New Ways for Image Manipulations: Color, Size and Structure

Ariel Shamir
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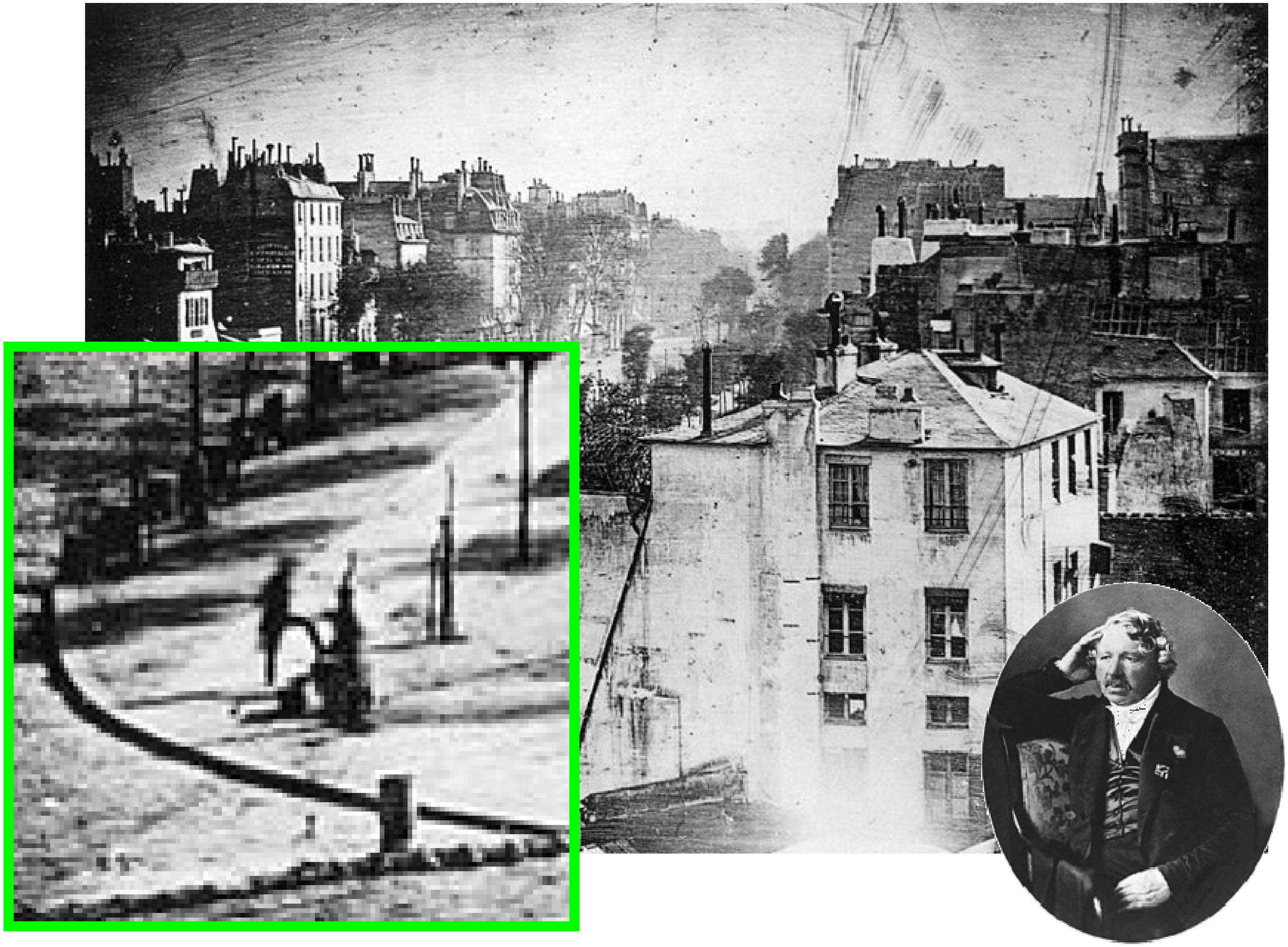
Israel

The Power of Images

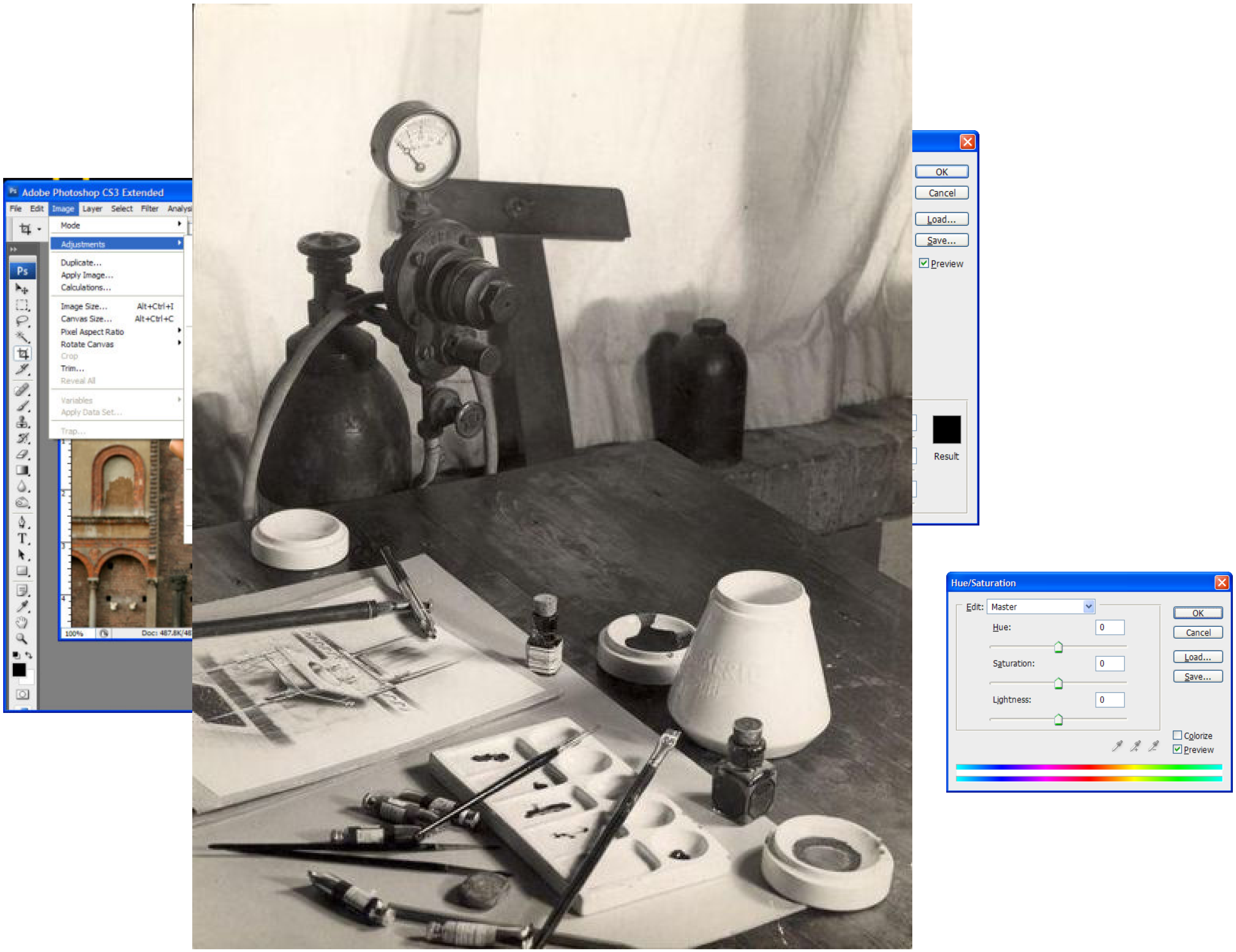
Earth as viewed from the Moon during the Apollo 8 mission, Christmas Eve, 1968



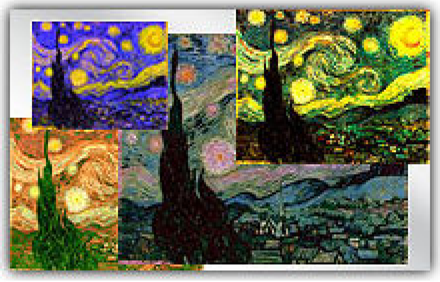
Paris~1838: Louis-Jacques-Mandé Daguerre

~ 1940

After 1940


Adobe Photoshop CS3 Extended
File Edit Image Layer Select Filter
Mode
Adjustments
Duplicate...
Apply Image...
Calculations...
Image Size... Alt+Ctrl+I
Canvas Size... Alt+Ctrl+C
Pixel Aspect Ratio
Rotate Canvas
Crop
Trim...
Reveal All
Variables
Apply Data Set...
Trap...
OK
Cancel
Load...
Save...
Preview
Result
Hue/Saturation
Edit: Master
Hue: 0
Saturation: 0
Lightness: 0
OK
Cancel
Load...
Save...
Colorize
Preview

Changing Colors



Lior Shapira · Ariel Shamir · Daniel Cohen-Or

Image Appearance Exploration by Model Based Navigation

Computer Graphics Forum, Volume 28, Number 2, Eurographics 2009

Recieved the Eurographics 2009 Second Best Paper Award!

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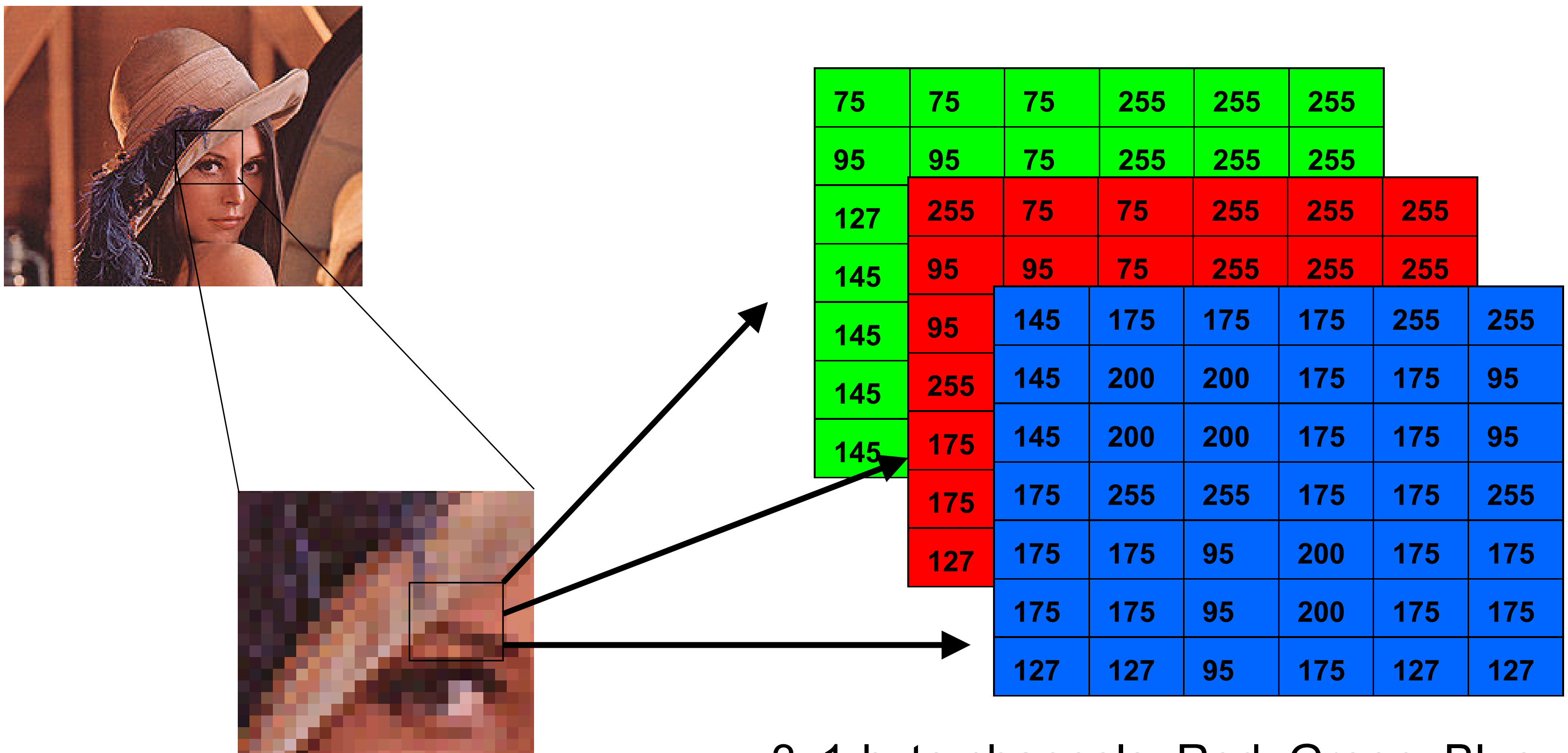
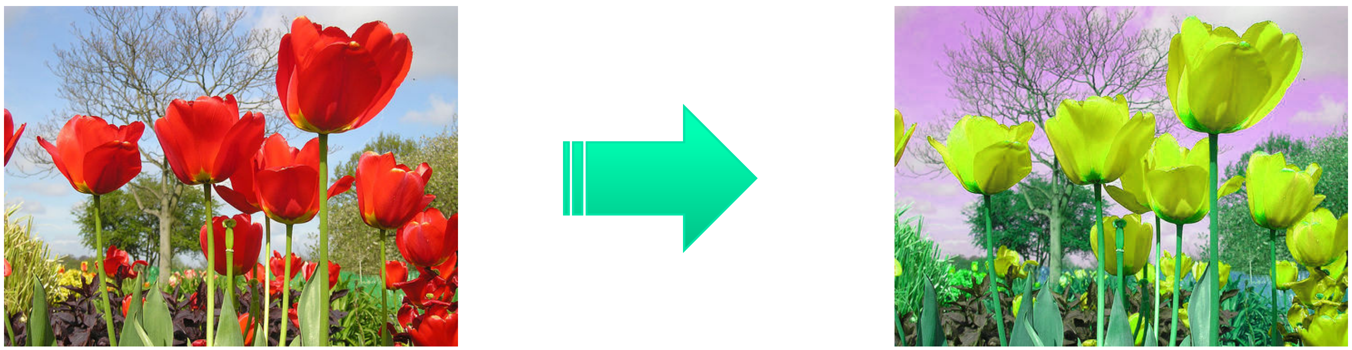
Color



3x1-byte channels: Red, Green, Blue

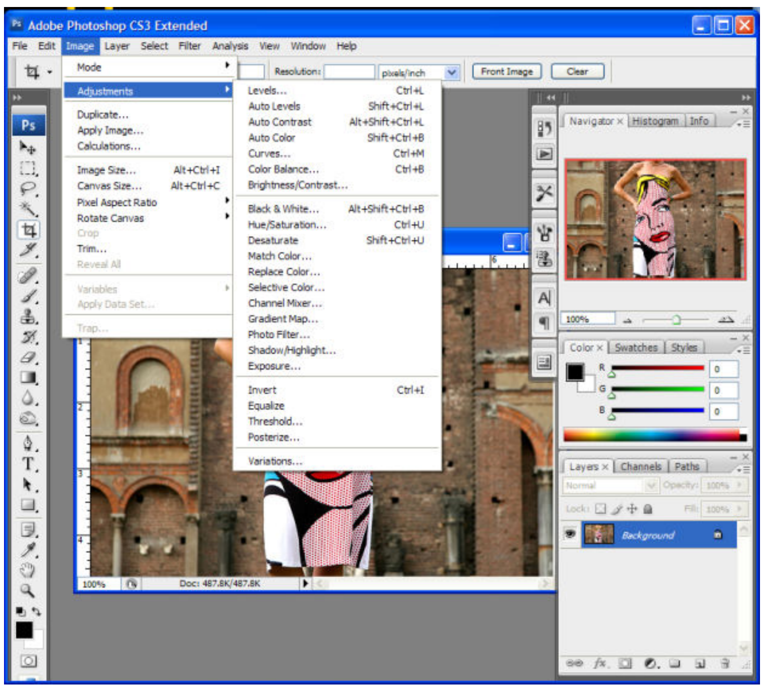
Changing Colors is Difficult

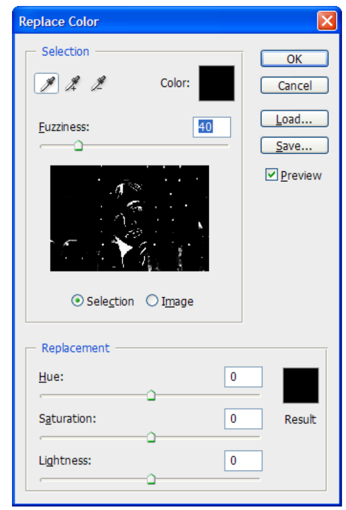
- Global changes → limited

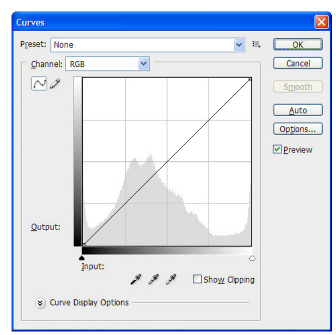


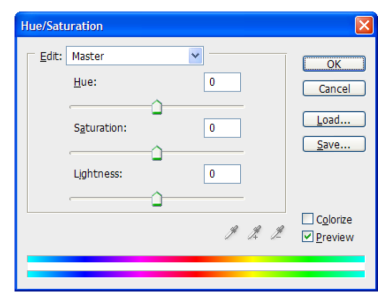
- Local changes → tend to create unrealistic artifacts

Changing Colors is Tedious



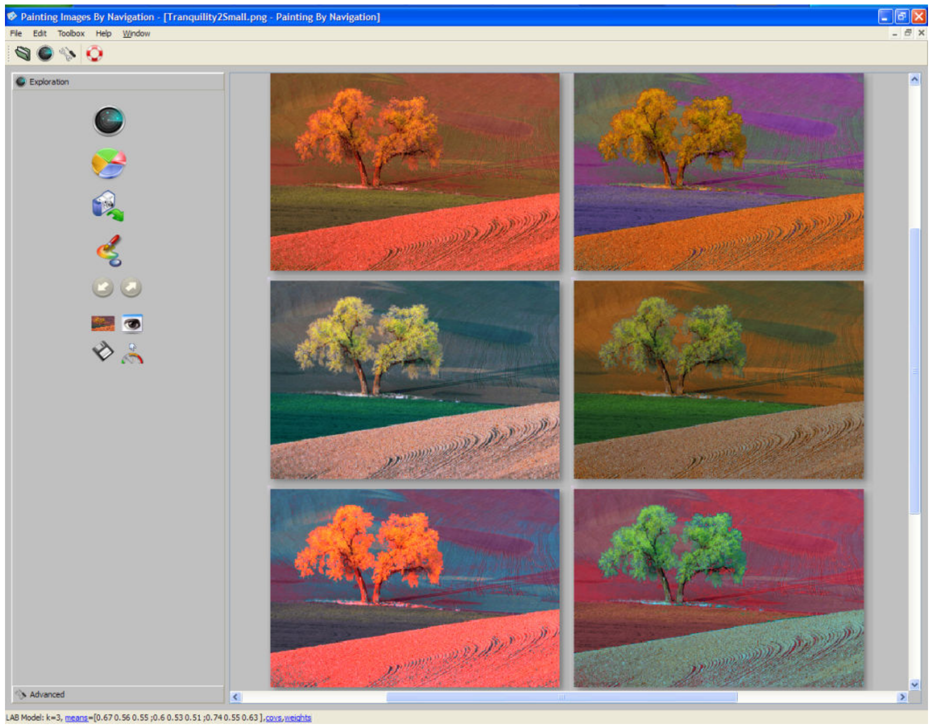






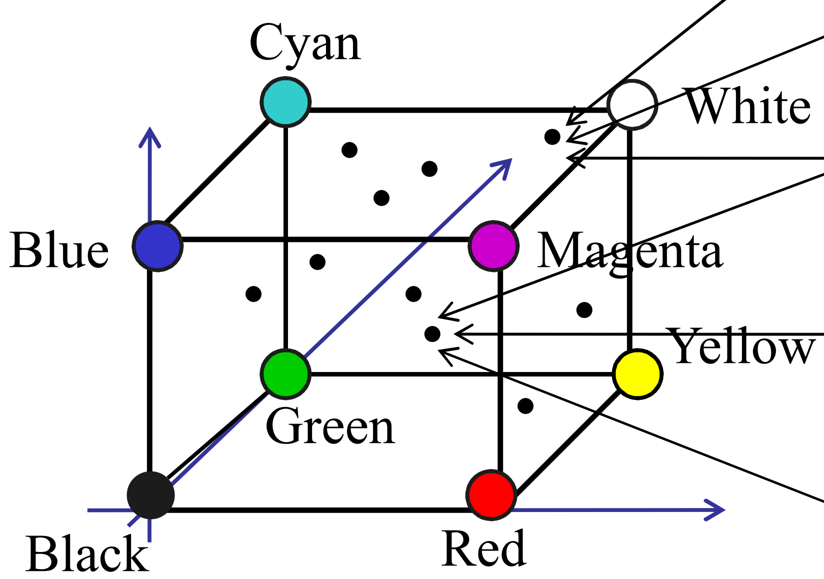
Change to What Color?

Our Approach

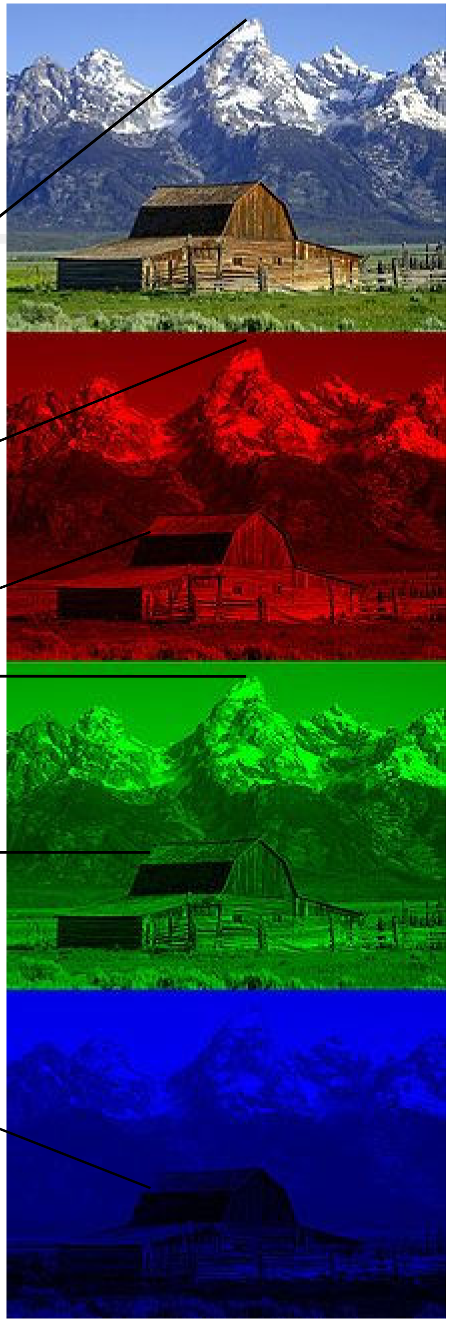


Representing Color

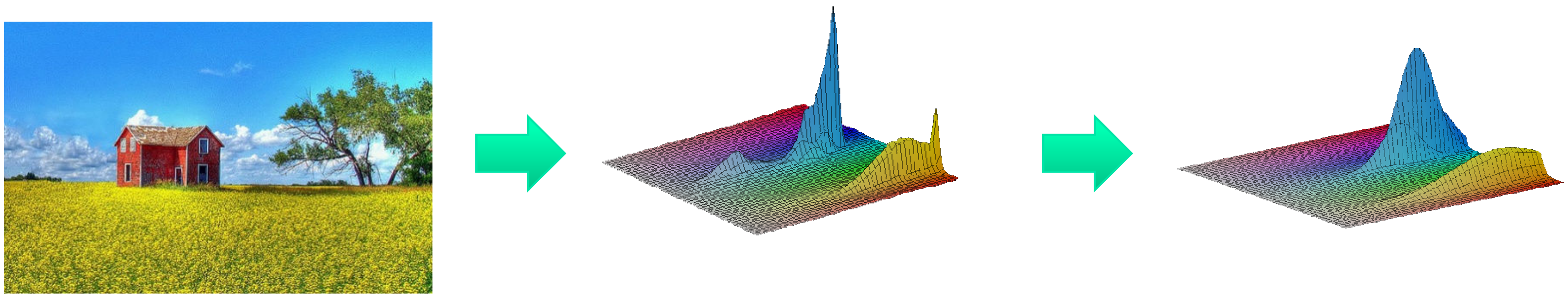
- Each Pixel can be seen as a 3D point in RGB space:



A 3D histogram of color values

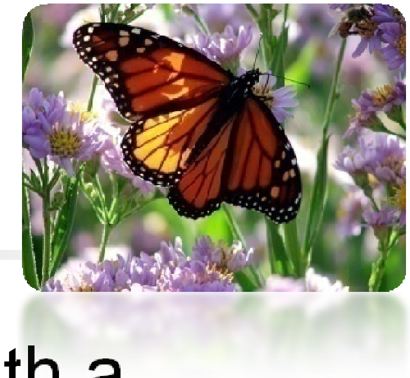


Part 1: Parametric Modeling of the Image Colors



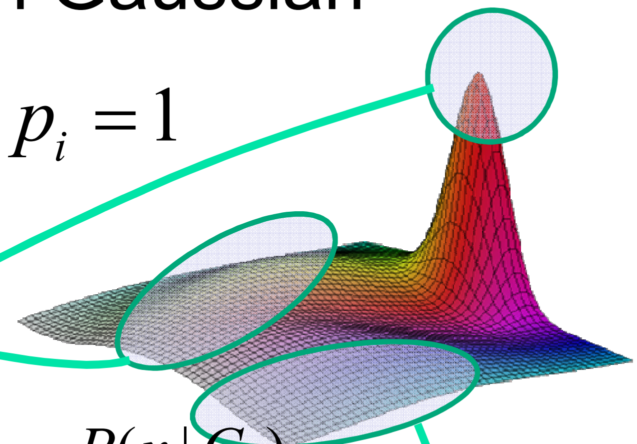
- More natural color spaces: HSV, Lab
- We use the 2D color channels and fit a Gaussian Mixture Model to the pixel colors histogram in these spaces

Association of Pixels



- Each pixel in the image is associated with a probability vector of matching each Gaussian

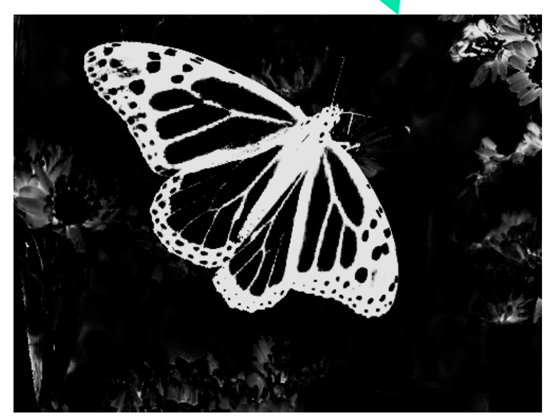
$$p = (p_1, \dots, p_k) \text{ s.t. } p_i = P(x \mid C_i), \sum_{i=1..k} p_i = 1$$



$P(x \mid C_1)$

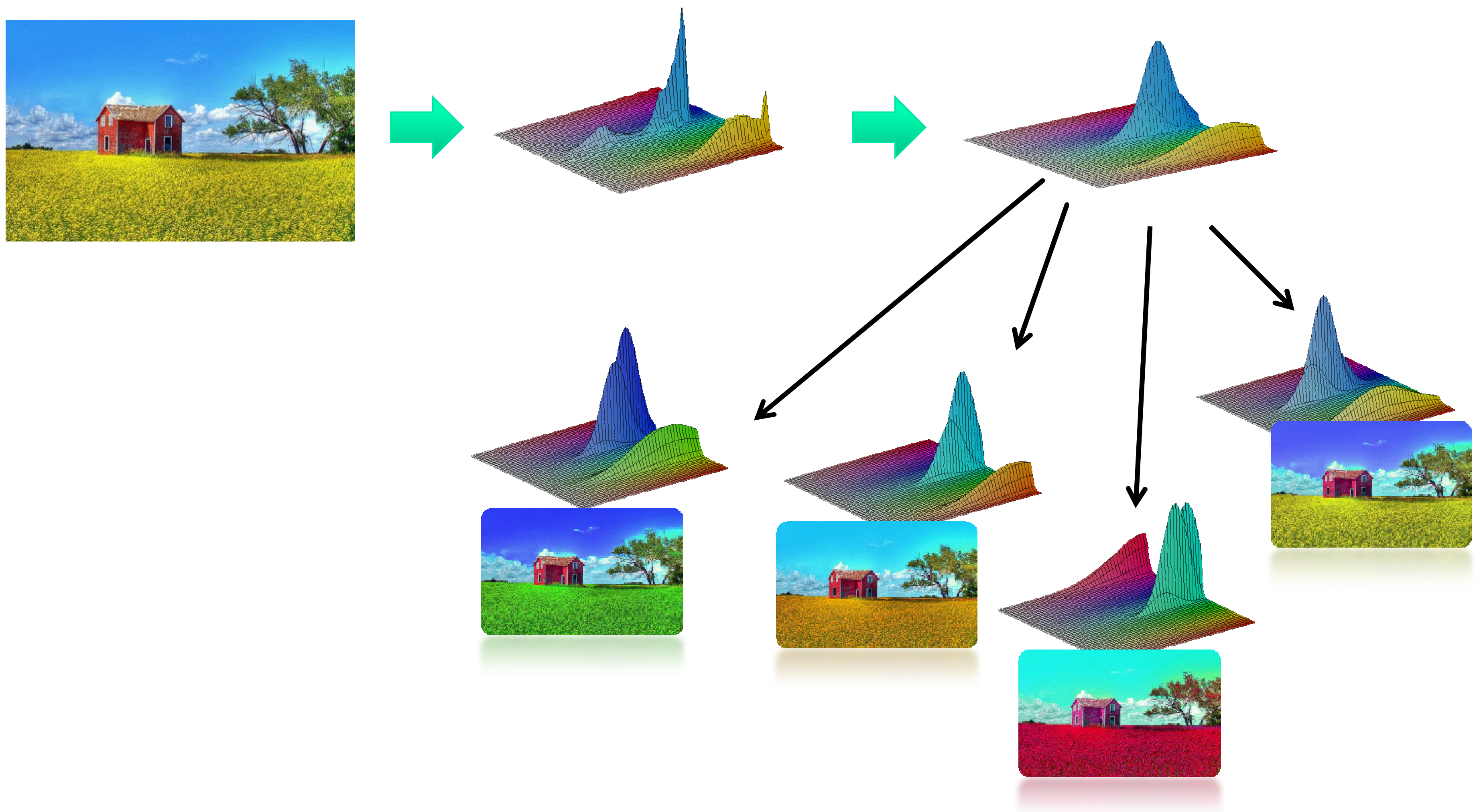
$P(x \mid C_2)$

$P(x \mid C_3)$

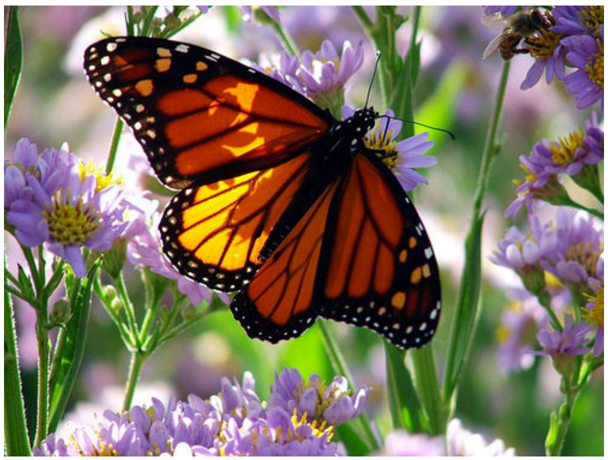


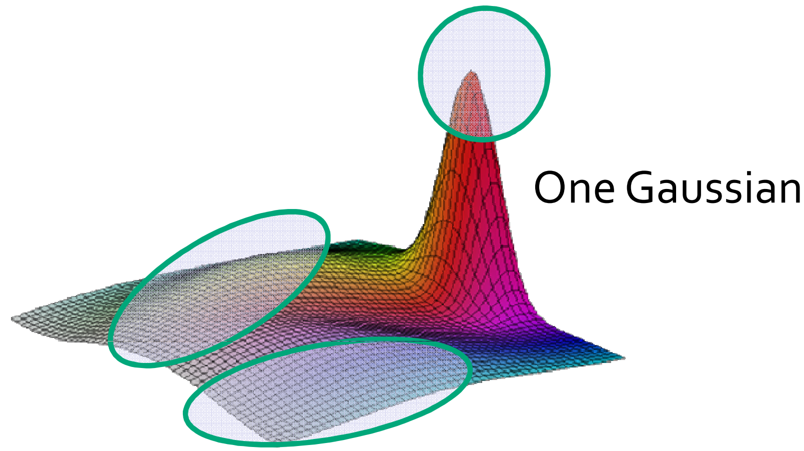
Key Idea

Changes in Model Parameters
Leads to a Change in the Image

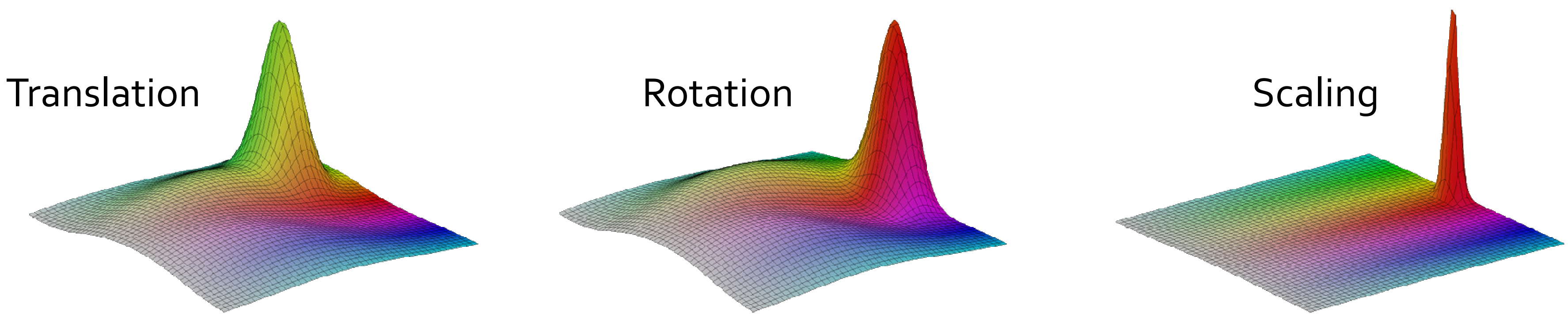


Model Parametric Changes





Gaussian Mixture Model, K=3



New Pixel Color

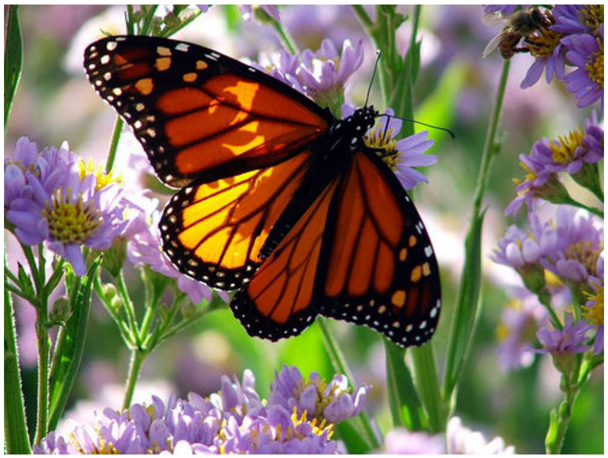
- After transformation, the Guassian $\sim N(\boldsymbol{\mu}_i, \mathbf{C}_i)$ has a new mean and covariance matrix $\sim N(\boldsymbol{\mu}_i^{new}, \mathbf{C}_i^{new})$
- A pixel color x is transformed by the operations on Guassian i as follows:

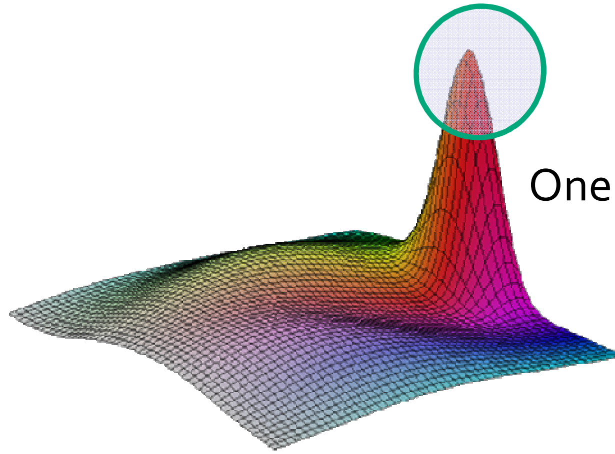
$$x_i = \mathbf{C}_i^{new} \cdot \mathbf{C}_i^{-1} \cdot \left((x - \boldsymbol{\mu}_i) + \boldsymbol{\mu}_i^{new} \right)$$

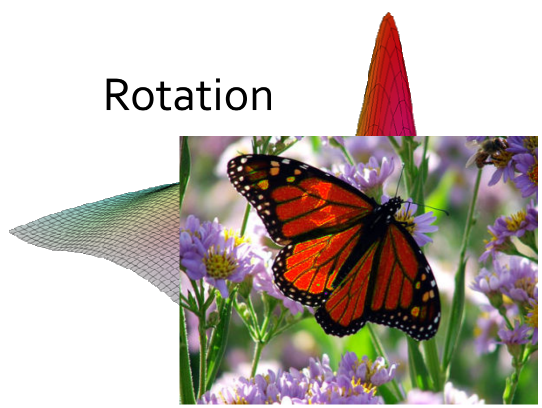
- The new pixel color is given by the weighted average of all new colors created by all Gaussians:

$$x^{new} = \sum_{i=1}^{k} p_i x_i$$

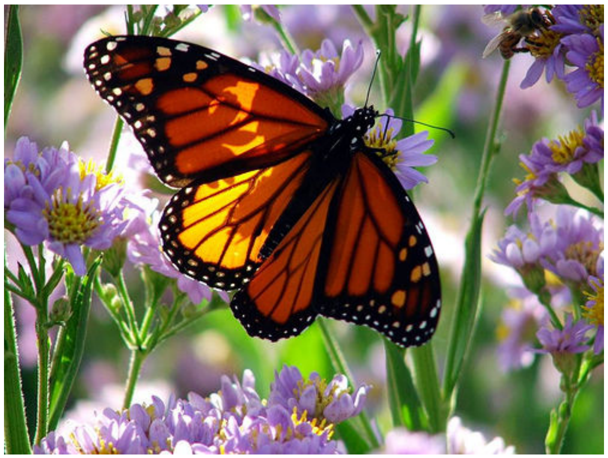
Synthesizing New Image: Simple Example

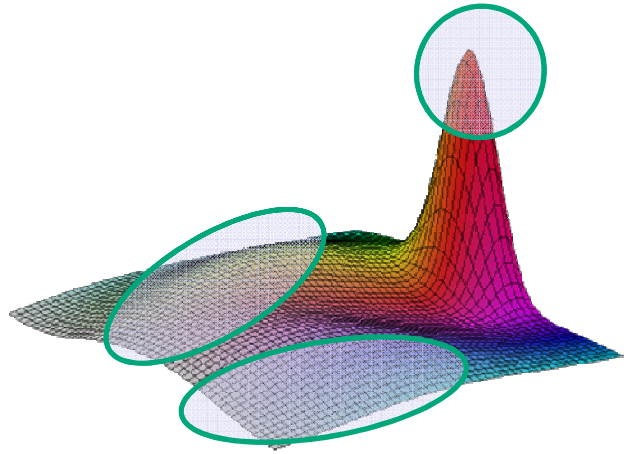




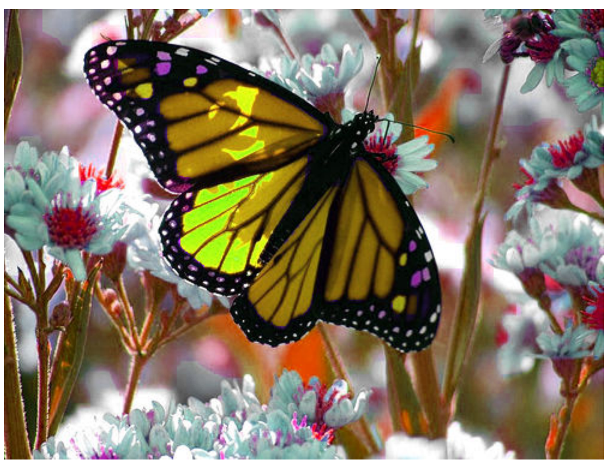


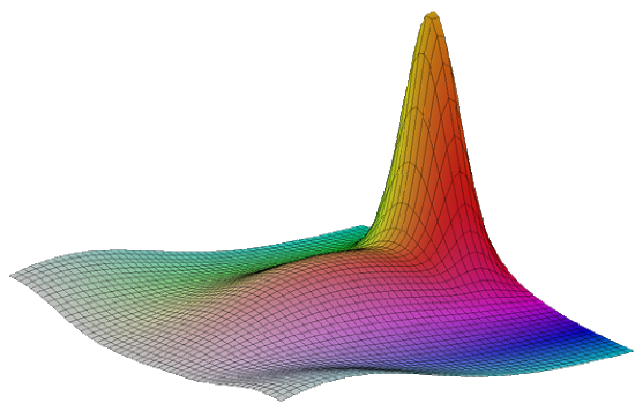
Combining Complex Transformation





Gaussian Mixture Model, K=3





Complex Transformation

Part II: Navigation in Appearance Space

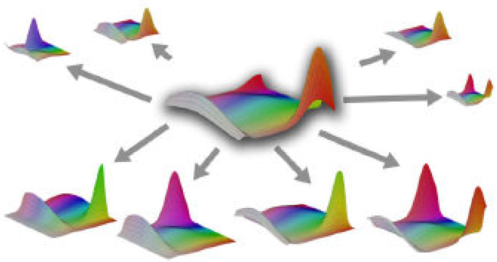
- Once we have a way to synthesize new images based on changing a parametric model we can build a simple algorithm:

```
10 Sample parametric space
20 Synthesize images
30 Display to user
40 Accept user feedback
50 Goto 10
```

User Interface Challenges

- How to display the image results?
- How to let the user interact with them?

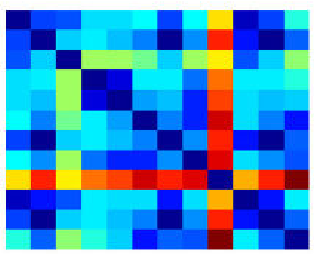
Map from High Dimension to 2D



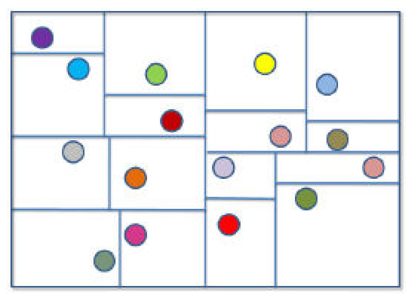
Sample Space

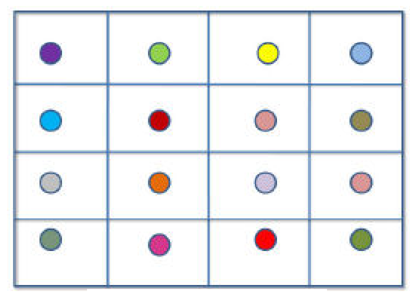
MDS

Grid layout



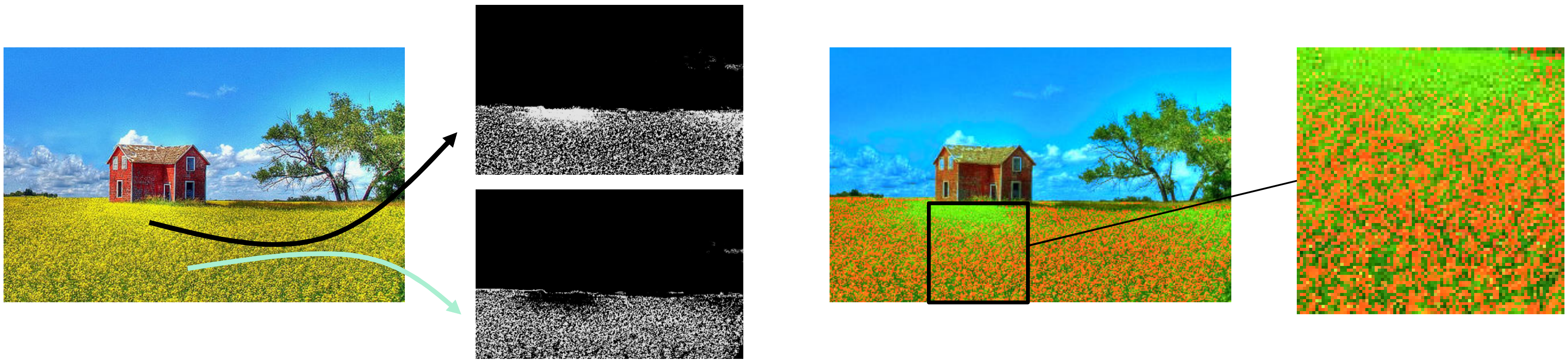
Affinity



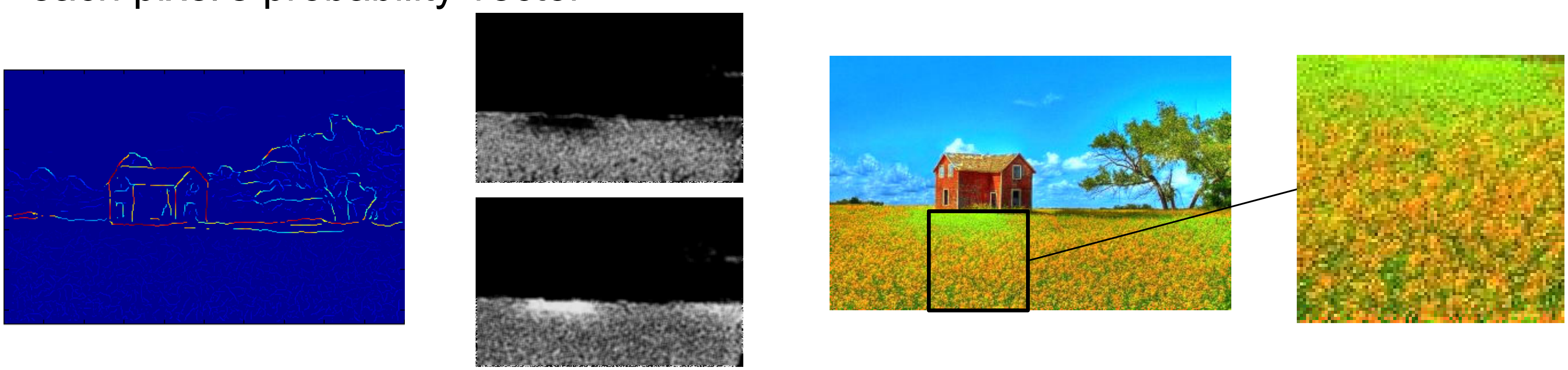


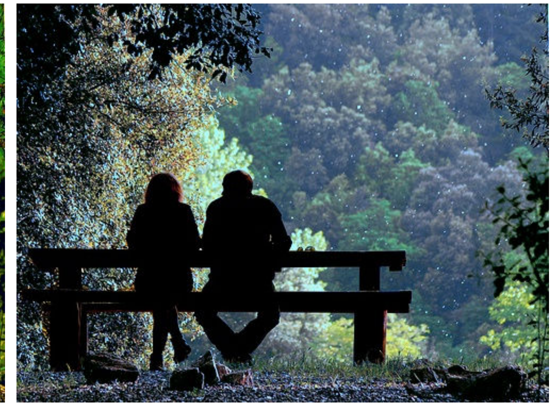
Spatial Considerations

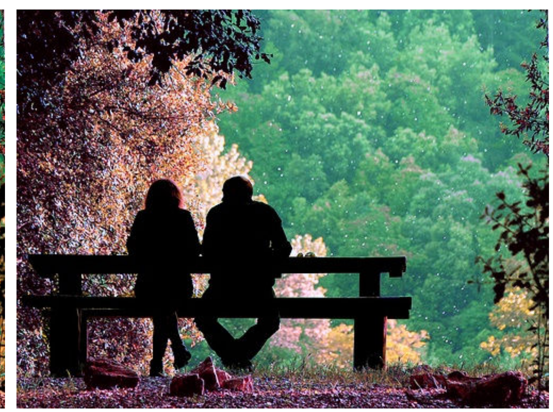
- Complex colors may cause **spatial artifacts**



- To reduce these, we use a natural edge map and apply a median-filter on each pixel's probability vector





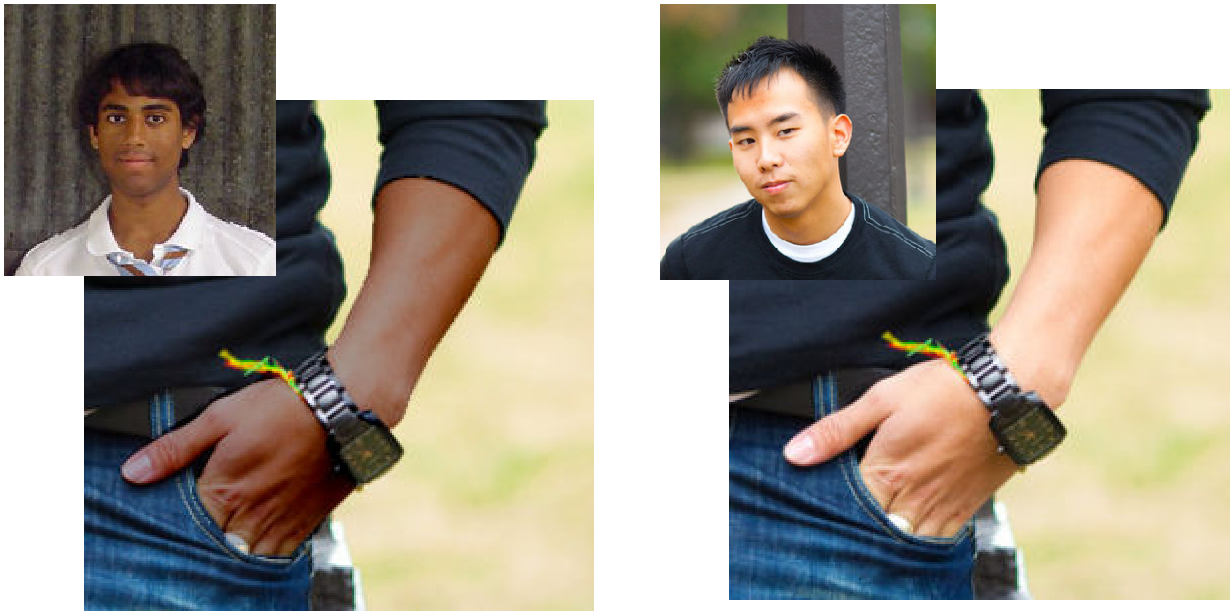


Other Use of Parametric Color Model

- Defining image regions to extract the head by defining the characteristic color of face (skin colors), hair (hair colors) and background.

Synthesize to Change Skin Color

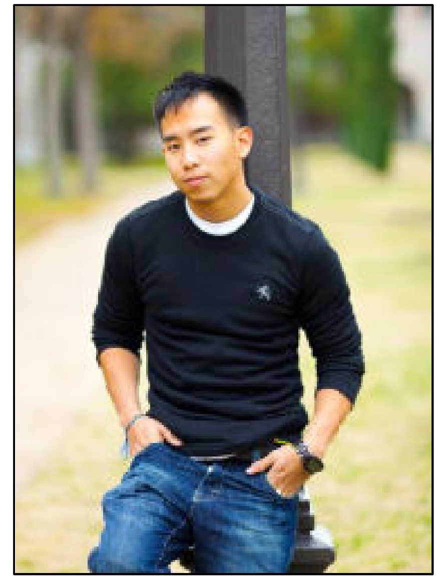
- Mapping the extracted face skin color to all skin regions:



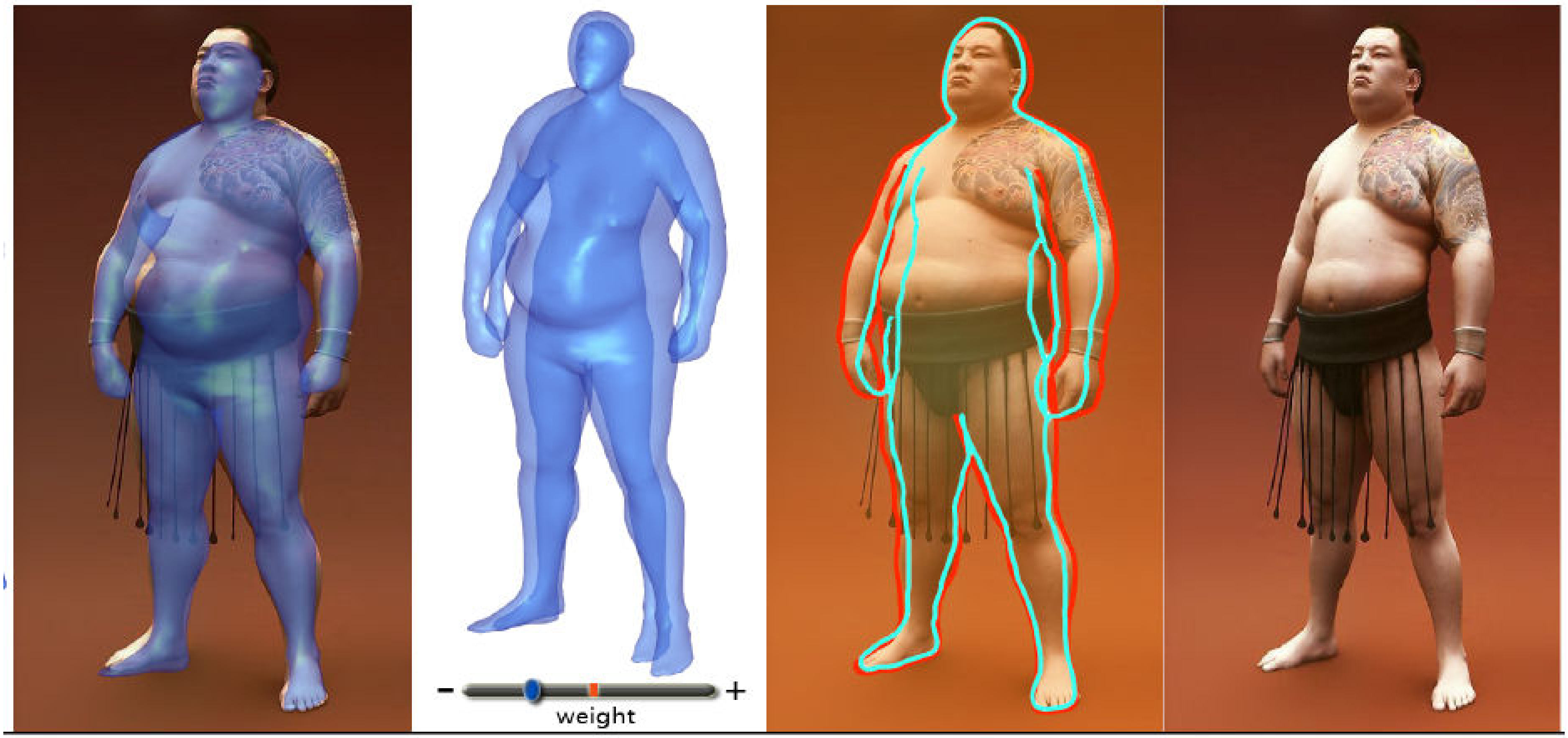
Identity Transfer

Identity Transfer

Image Composition



Shape Retargeting



Which is Fake?

Which is Fake?

Changing Size

Michael Rubinstein · Ariel Shamir · Shai Avidan

Multi-operator Media Retargeting

ACM Transactions on Graphics, Volume 28, Number 3, SIGGRAPH 2009

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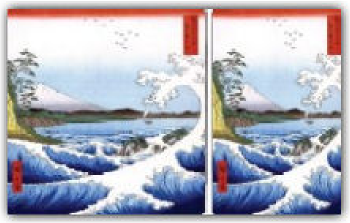

Ariel Shamir · Shai Avidan

Seam Carving for Media Retargeting

Communications of the ACM, Volume 52, Number 1, Pages 77-85, January 2009

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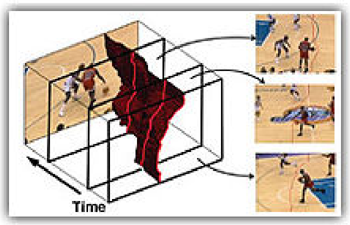

Michael Rubinstein · Ariel Shamir · Shai Avidan

Improved Seam Carving for Video Retargeting

ACM Transactions on Graphics, Volume 27, Number 3, SIGGRAPH 2008

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Shai Avidan · Ariel Shamir

Seam Carving for Content-Aware Image Resizing

ACM Transactions on Graphics, Volume 26, Number 3 SIGGRAPH 2007

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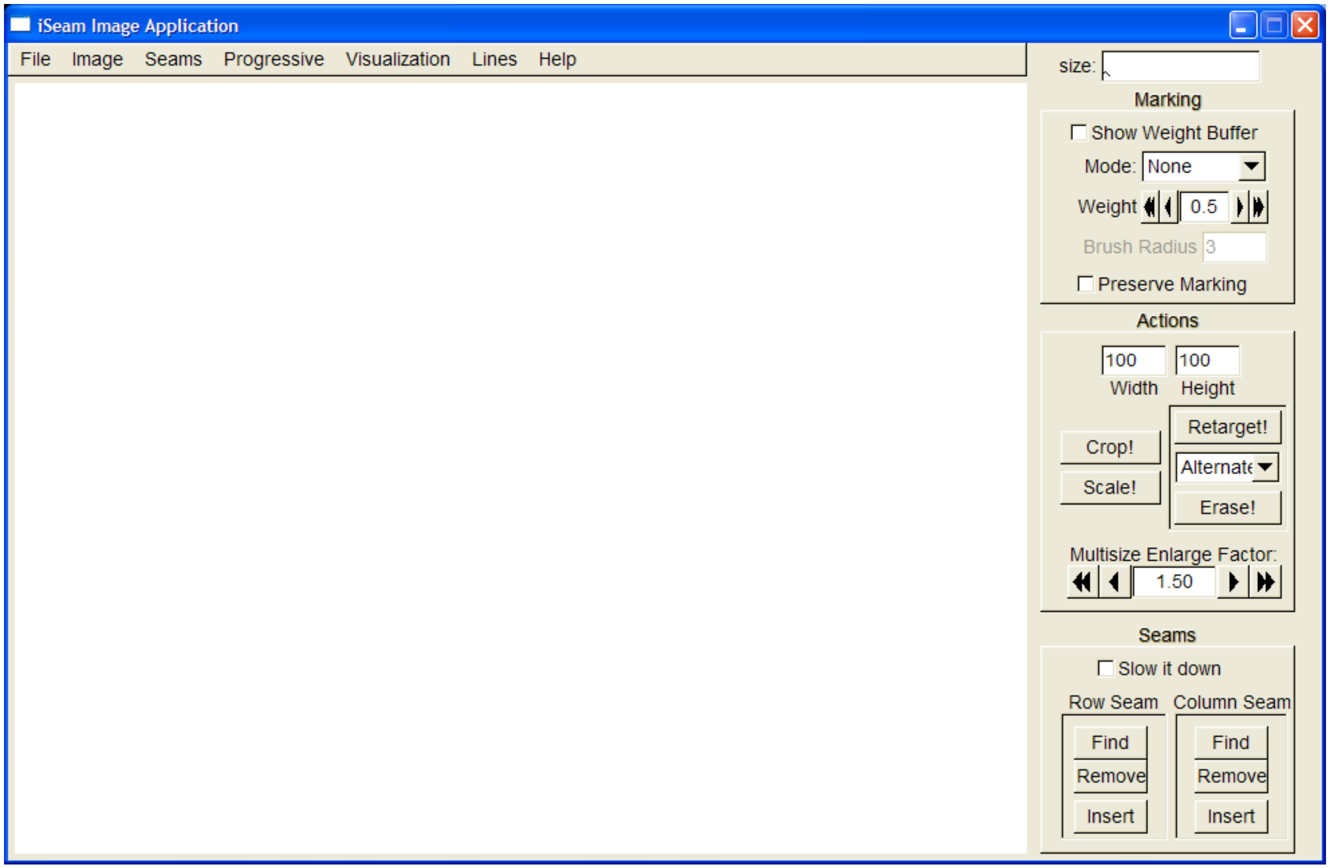
Content Aware

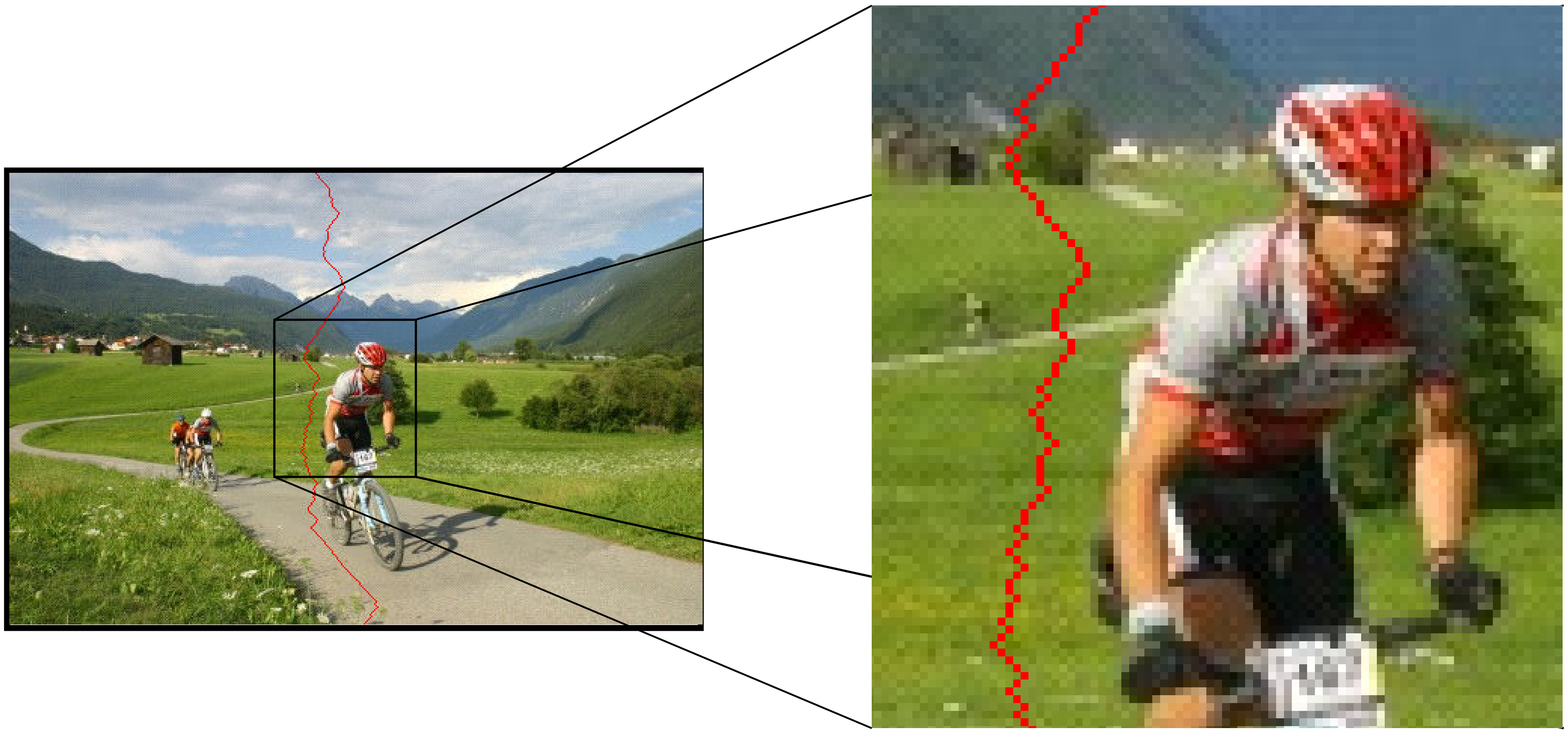
Scale

Crop

Our Approach



A Seam

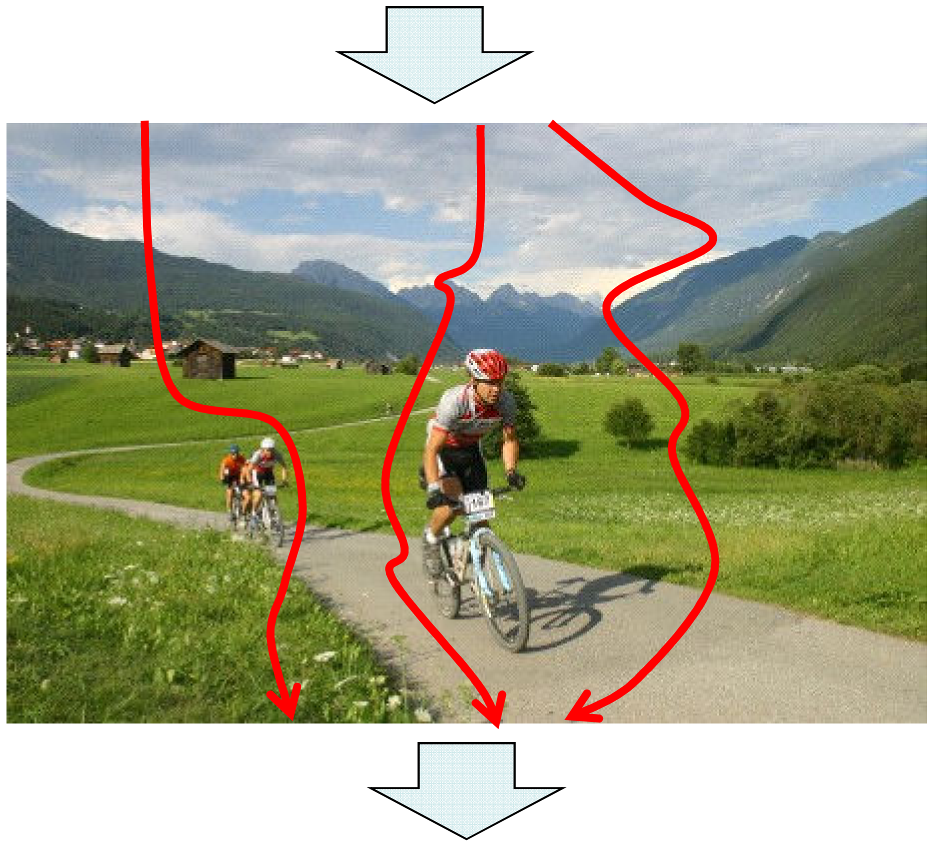


Seam Carving

A Local Operator!

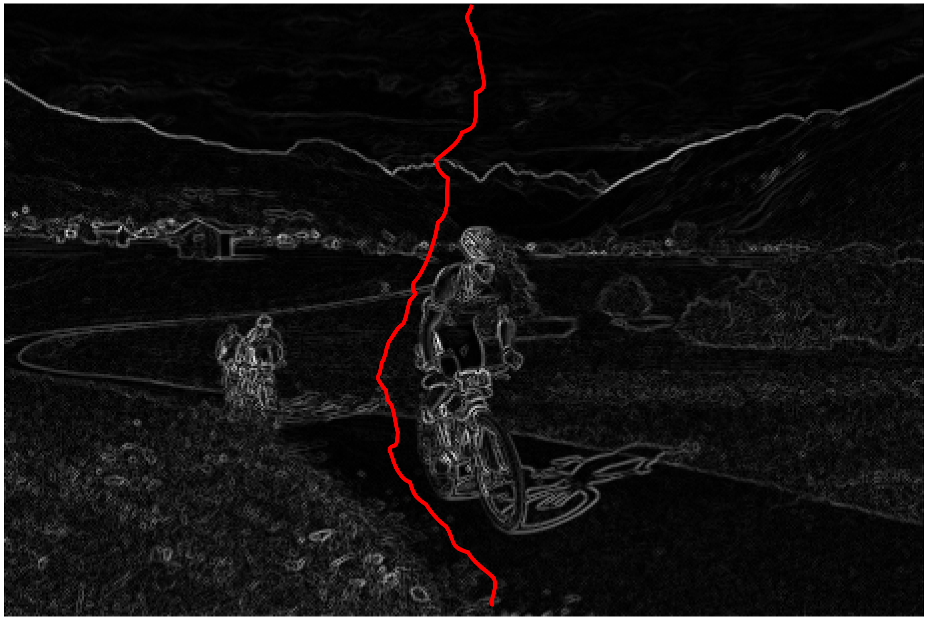
Width is
one pixel smaller

Finding the Seam?



The Optimal Seam

$$E(\mathbf{I}) = \left|\frac{\partial}{\partial x}\mathbf{I}\right| + \left|\frac{\partial}{\partial y}\mathbf{I}\right| \quad \Rightarrow \quad s^{*} = \arg\min_{s} E(s)$$



How Many Possible Seams?

- An image has n columns and m rows
- Start from any pixel at top row (n)
- For each one choose between 3 possible pixels in the next row
- For each one of those, choose between 3 in the next row…
- $n*3^{m-1}$ = exponential! ☹

Pixel Attribute → Dynamic Programming

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	2	3	9
7	3	4	2
5	4	7	8

Dynamic Programming

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	2+5	3	9
7	3	4	2
5	4	7	8

Dynamic Programming

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	7	3+3	9
7	3	4	2
5	4	7	8

Dynamic Programming

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	7	6	12
14	9	10	8
14	13	15	8+8

Searching for Minimum

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	7	6	12
14	9	10	8
14	13	15	16

$\uparrow$

Backtracking the Seam

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	7	6	12
14	9	10	8
14	13	15	16

Backtracking the Seam

$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

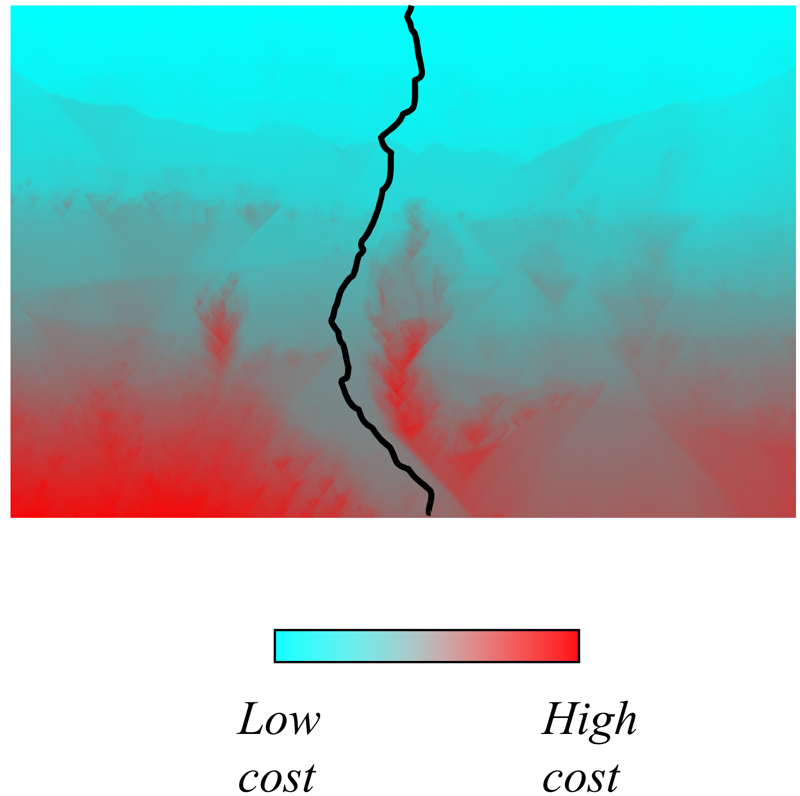
5	8	12	3
9	7	6	12
14	9	10	8
14	13	15	16

Backtracking the Seam

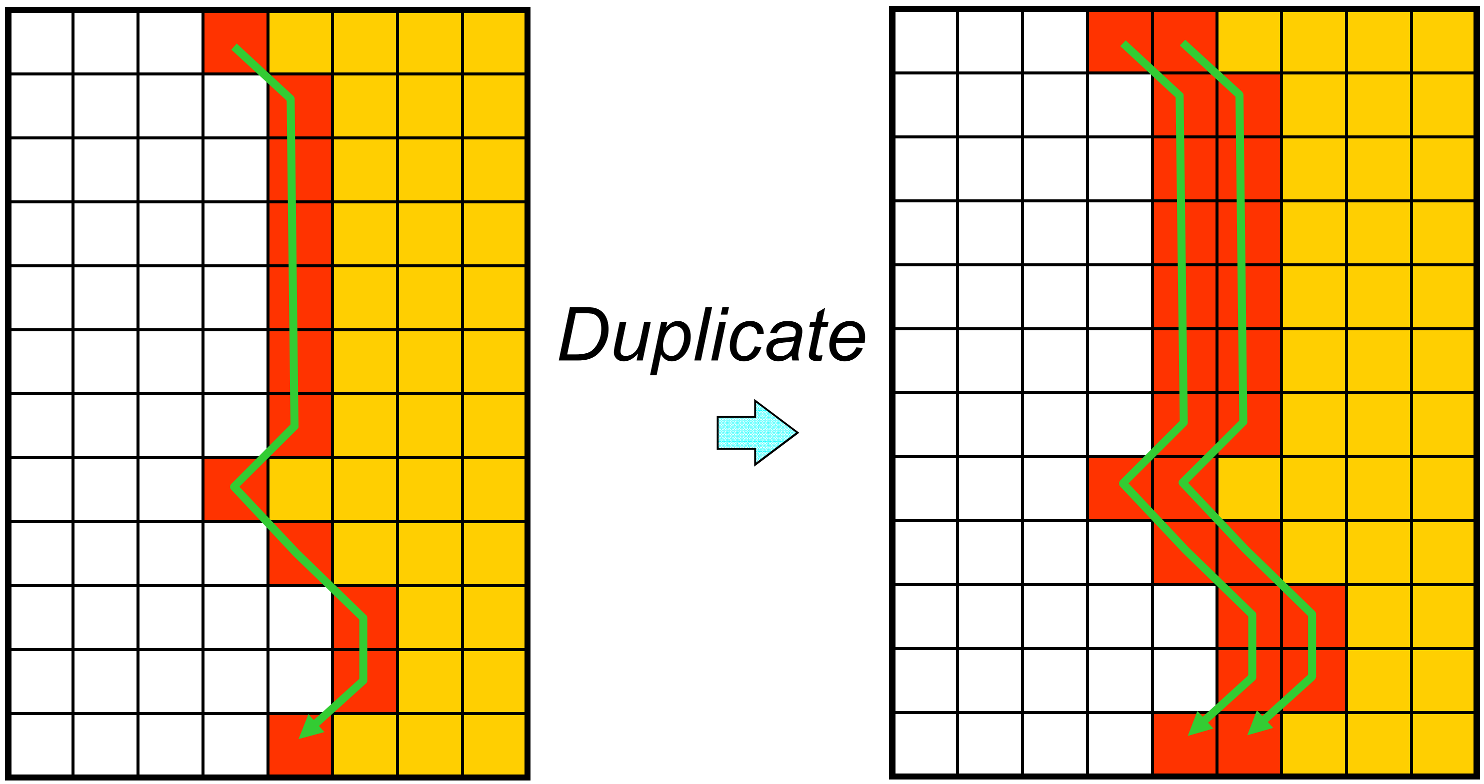
$$M(i, j) = e(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

5	8	12	3
9	7	6	12
14	9	10	8
14	13	15	16

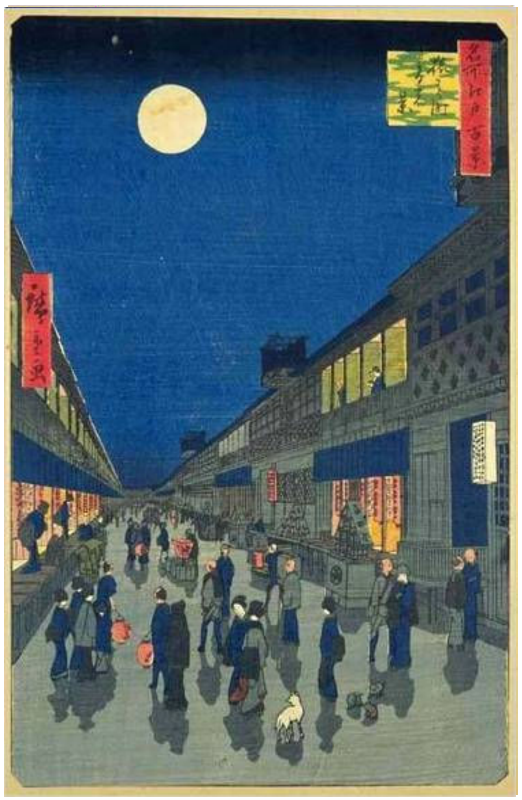
The Cost Matrix & Seam

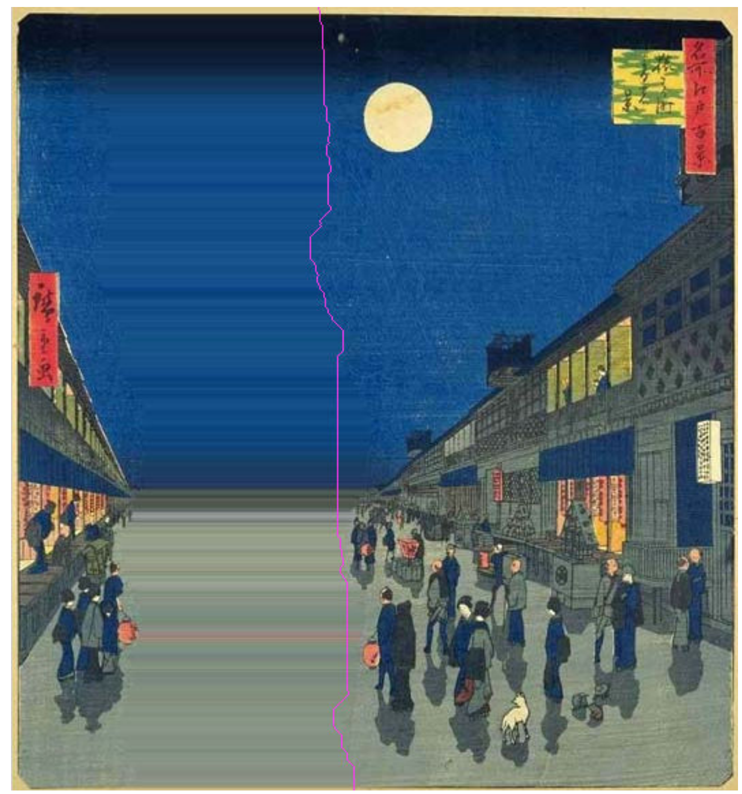


Inserting a Seam?

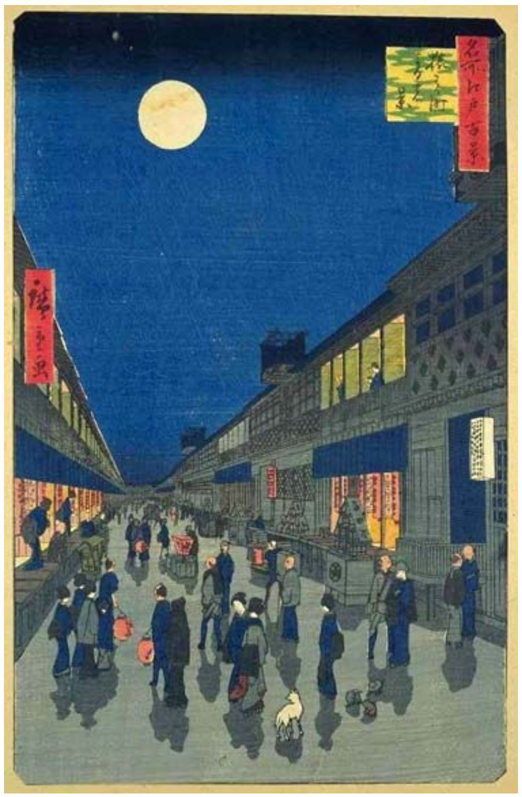


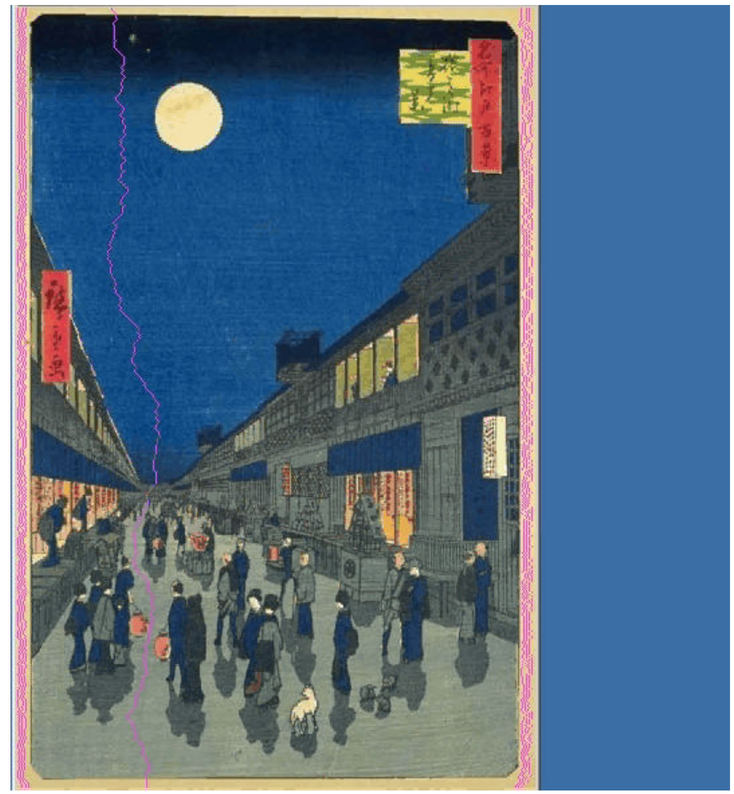
Width is one pixel larger



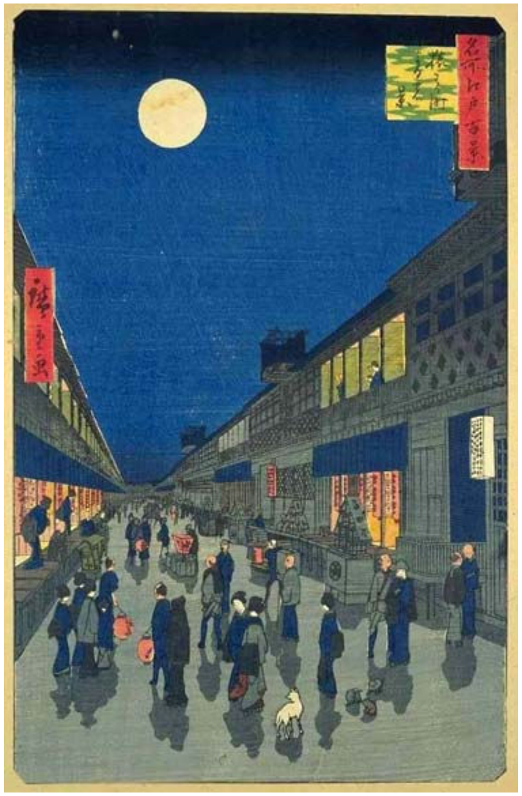


Duplicate Seams in Order





Duplicate Seams in Order



Enlarged or Reduced?

Not Always a Success

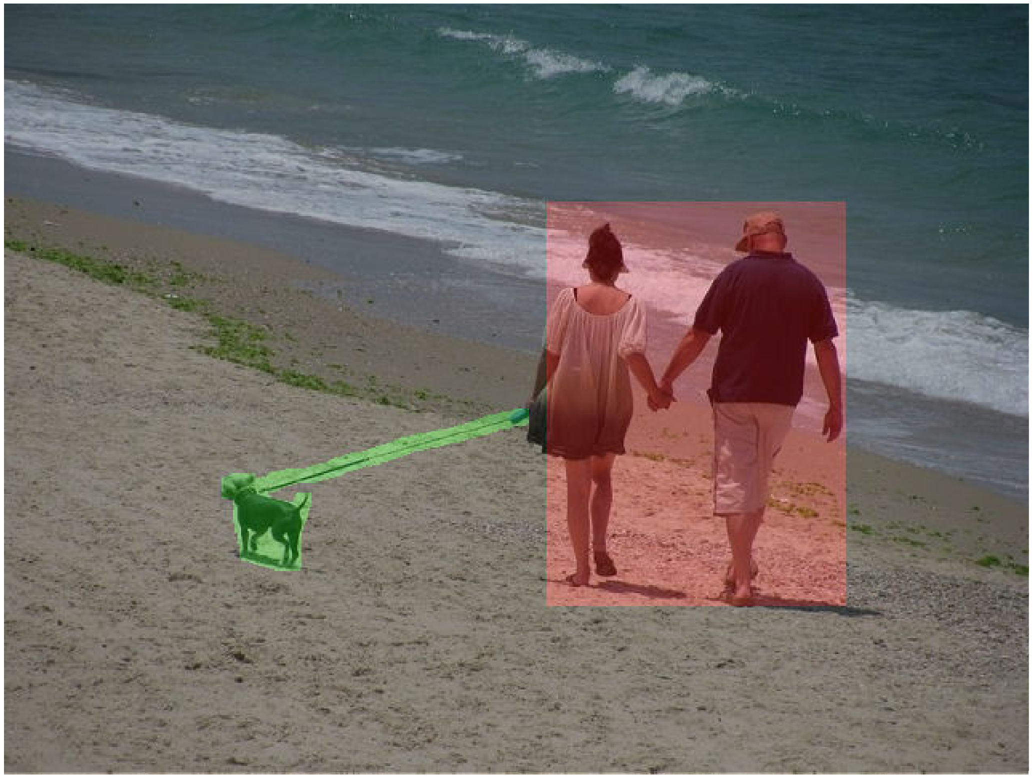
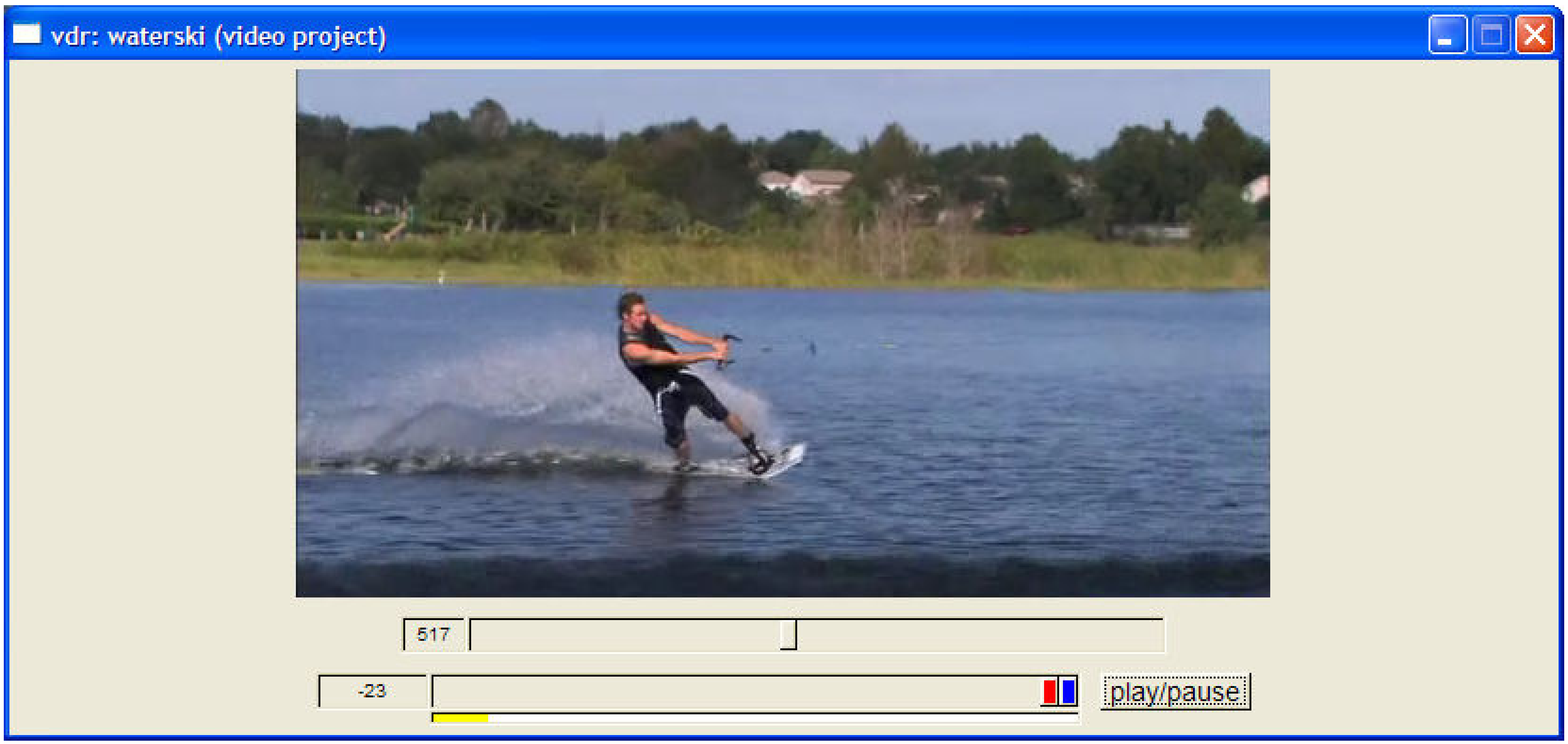


Image: Yehudit Garinkol

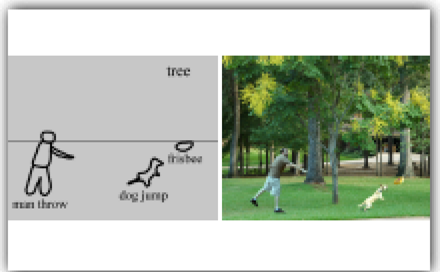
Find the Missing Shoe!

Solution

Video As Well



Fabricating an Whole Image

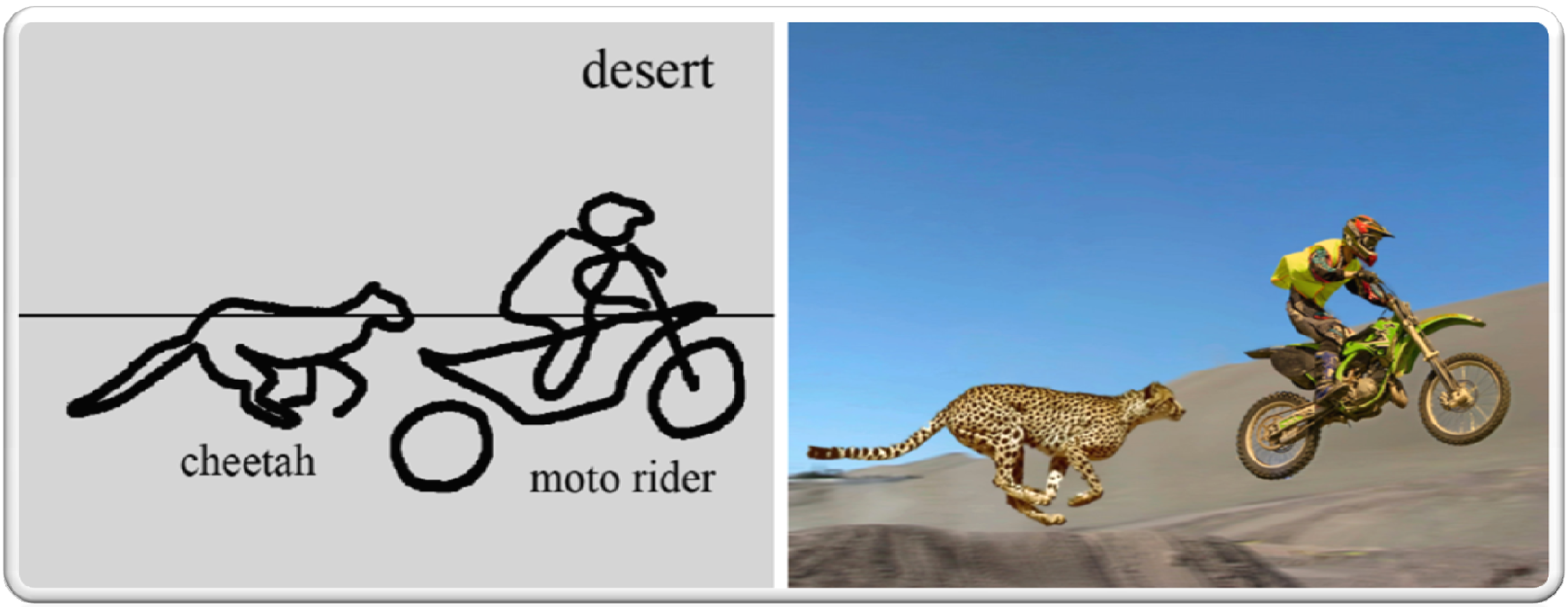


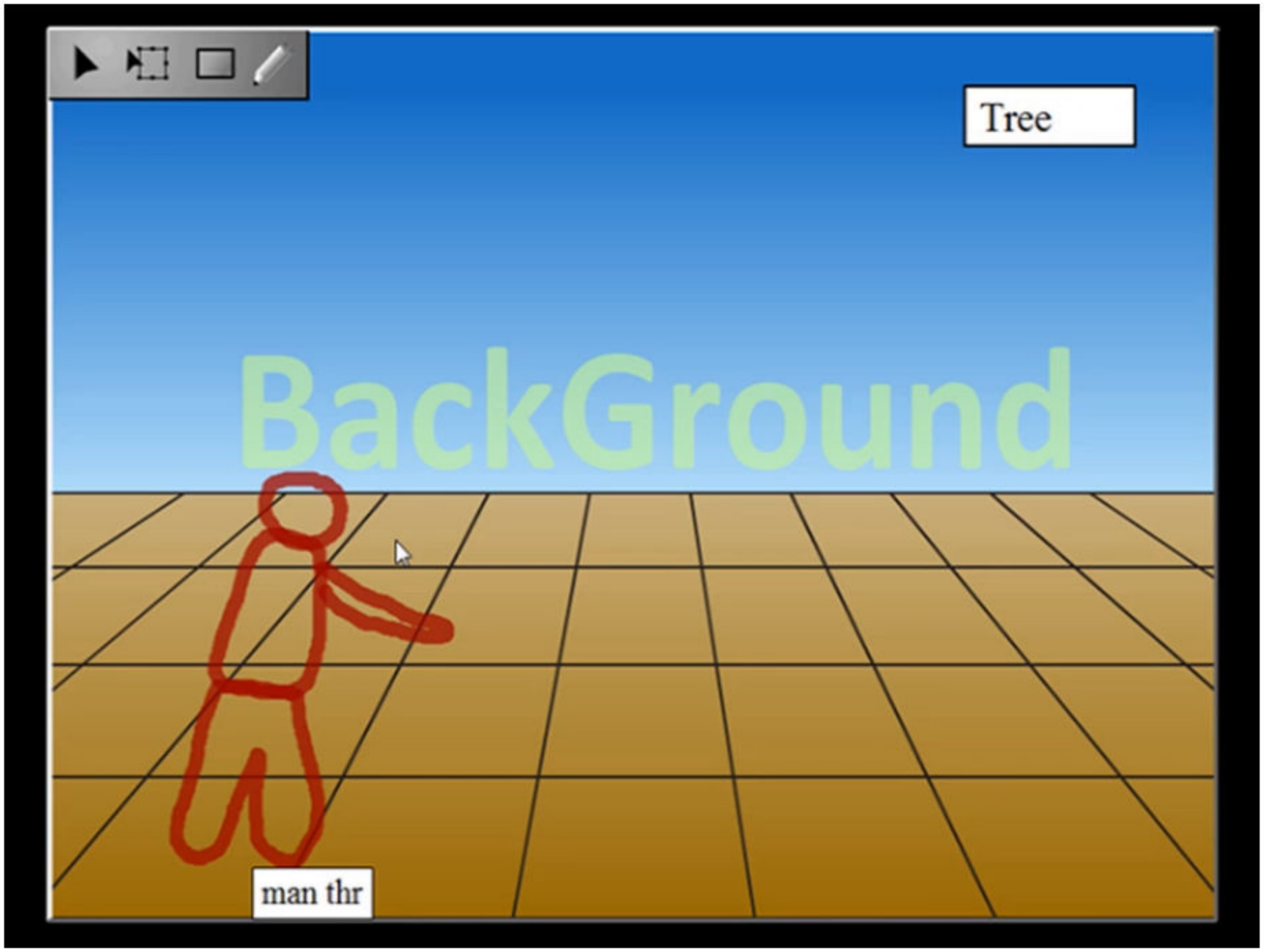
Tao Chen · Cheng Ming Ming · Ping Tan · Ariel Shamir · Shi-Min Hu

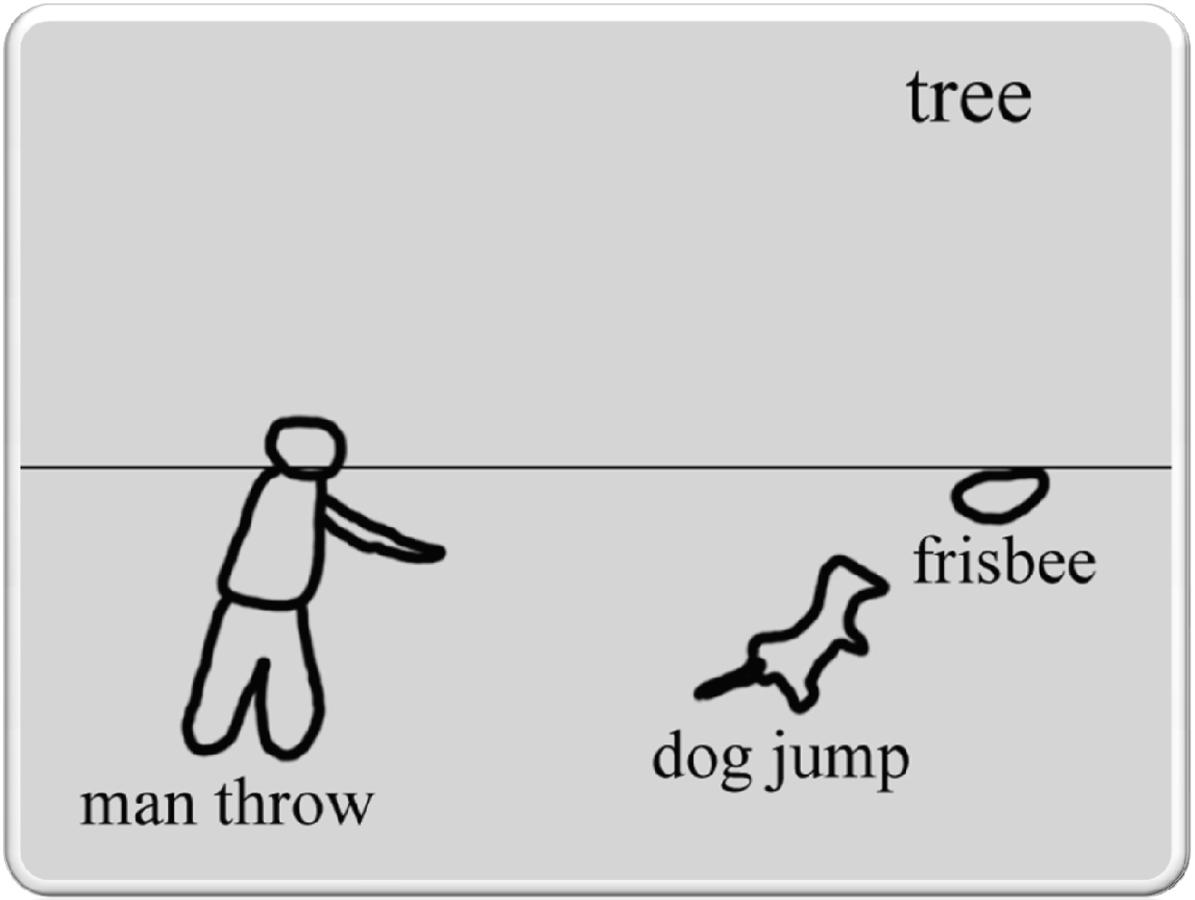
Sketch2Photo: Internet Image Montage

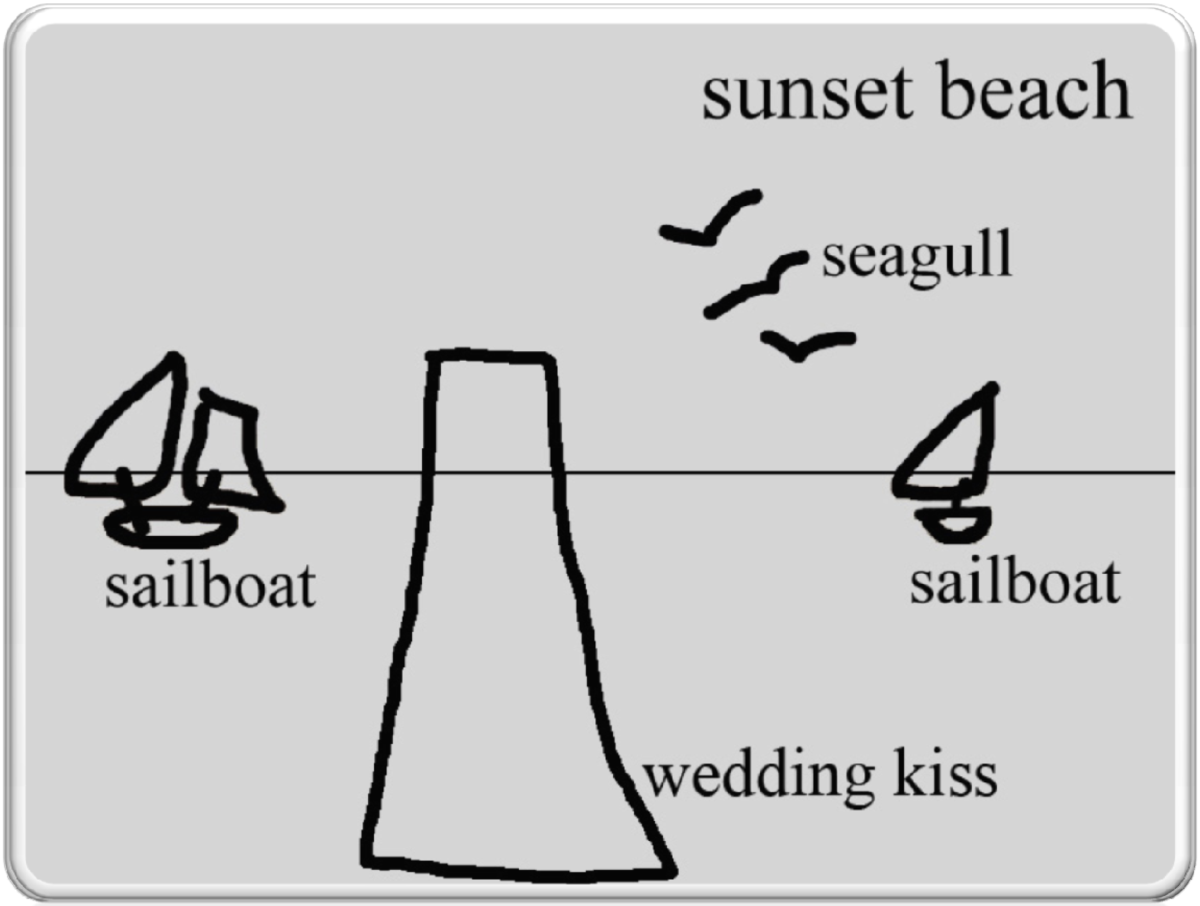
ACM Transactions on Graphics, Volume 28, Number 5, SIGGRAPH ASIA 2009

BibTeX More »

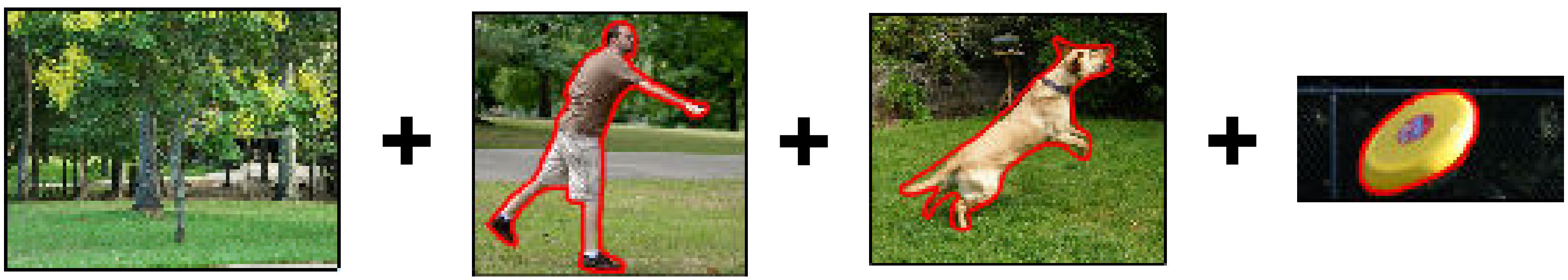



Tree
BackGround
man thr

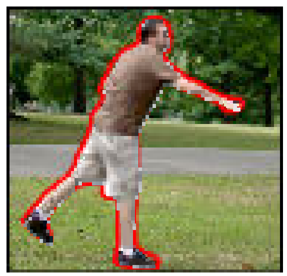
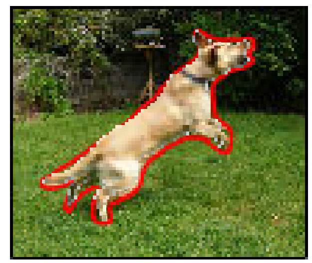

tree
frisbee
dog jump
man throw


sunset beach
seagull
sailboat
sailboat
wedding kiss

Find,



Find, Cut & Paste

 +  +  +  =

Challenges

- Image search
- Image comparison
- Image segmentation
- Image composition

  All Very difficult problems in general!
- Key idea:

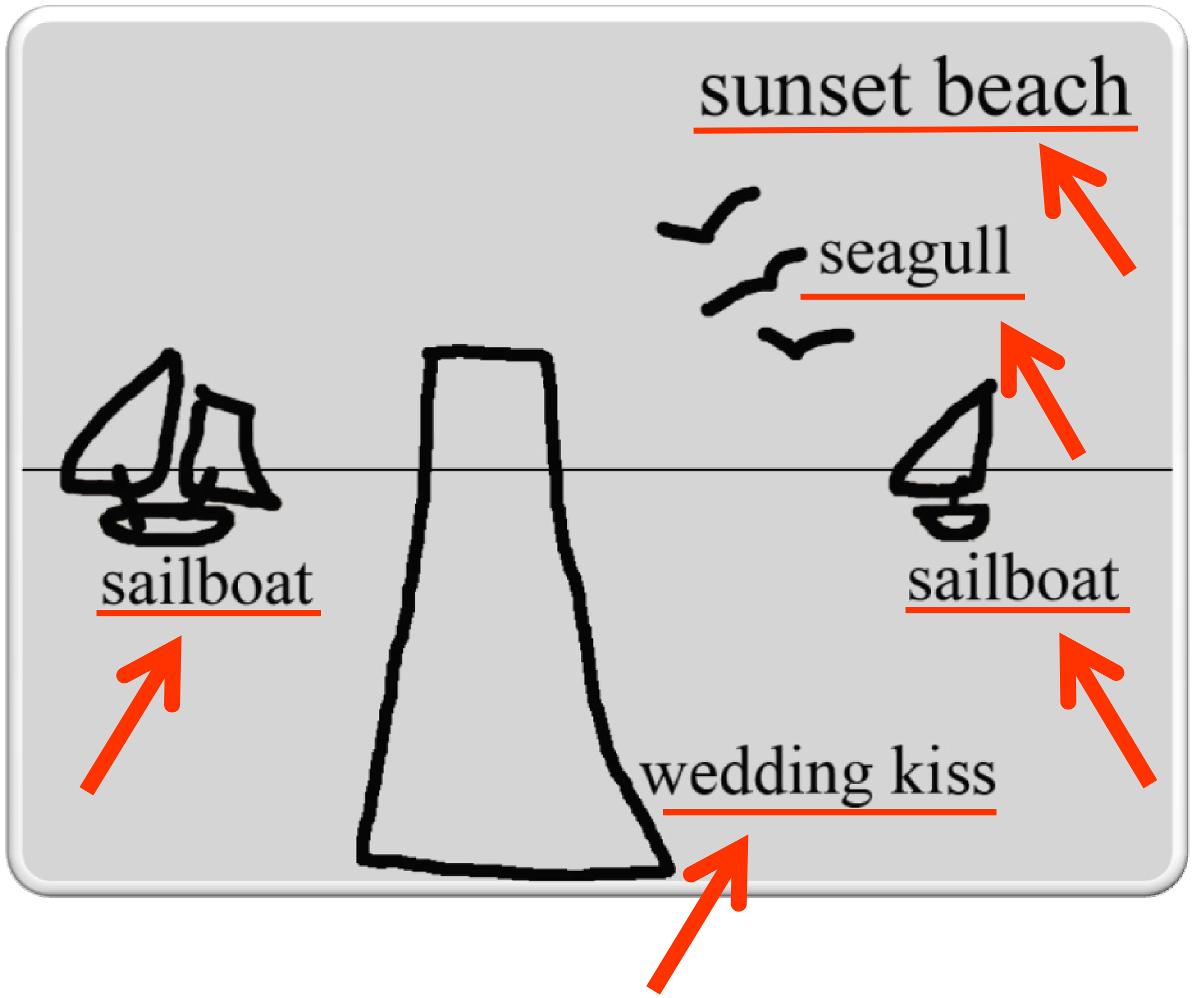
  Make the problems simpler by using simple images!

  → Extensive filtering

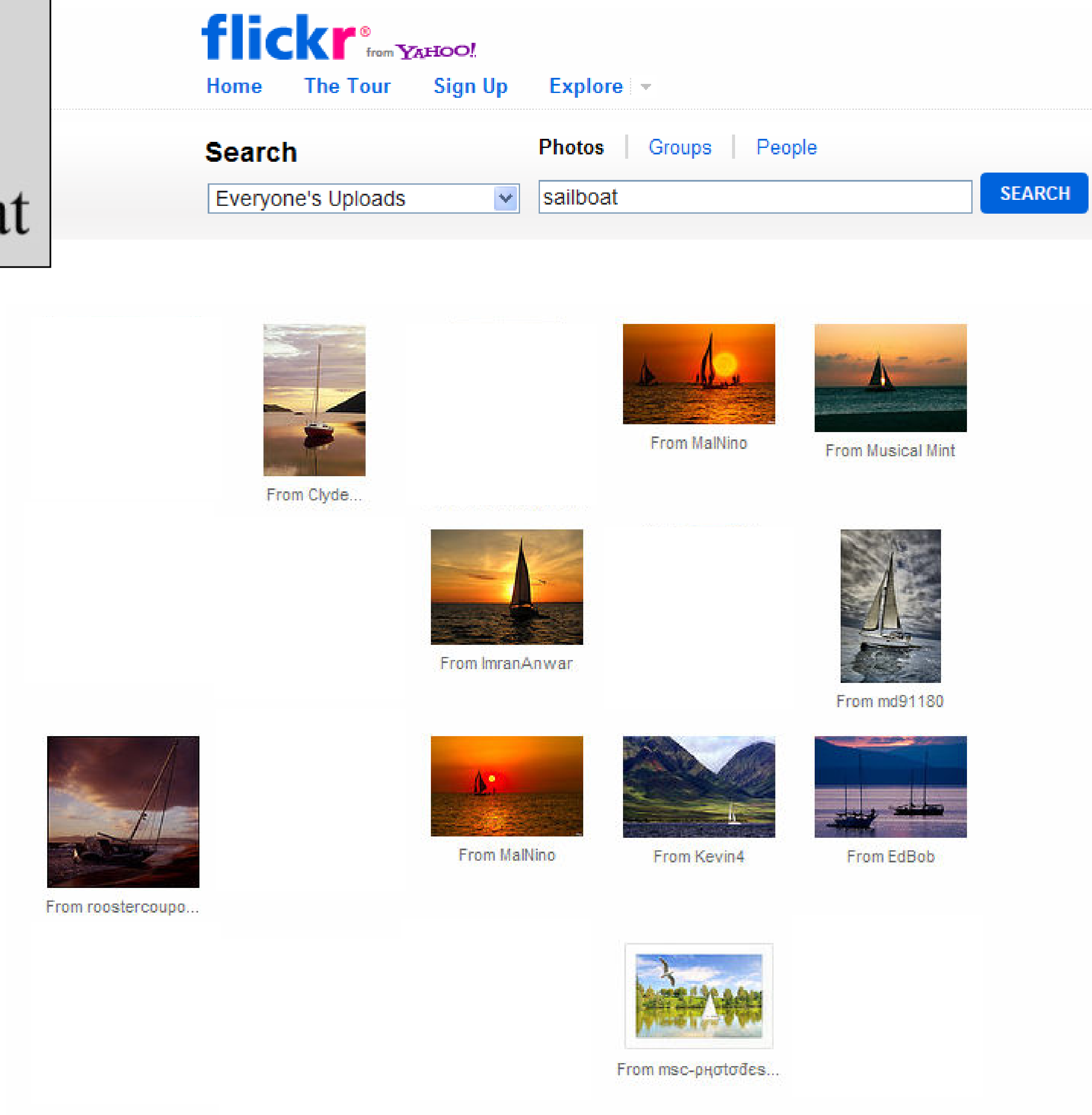
Find?

Where do you find anything today?

Google™ flickr® from YAHOO!


sunset beach
seagull
sailboat
sailboat
wedding kiss

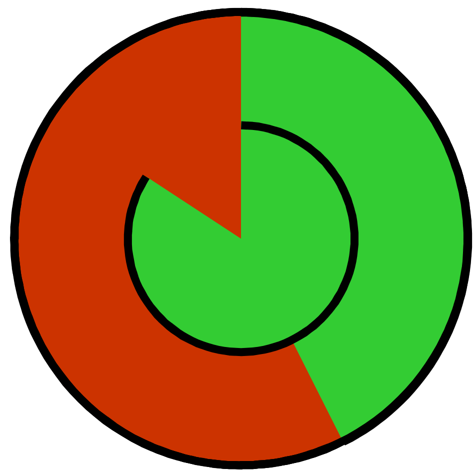

sailboat


flickr from YAHOO!
Home
The Tour
Sign Up
Explore
Search
Photos
Groups
People
Everyone's Uploads
sailboat
SEARCH
From Clyde...
From MalNino
From Musical Mint
From ImranAnwar
From md91180
From roostercoupo...
From MalNino
From Kevin4
From EdBob
From msc-pнσтσdes...

Filtering

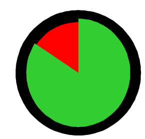
Query:

Shape Filtering



Filtering

- Small total number but large ratio of "good images" (around 80%-90%)



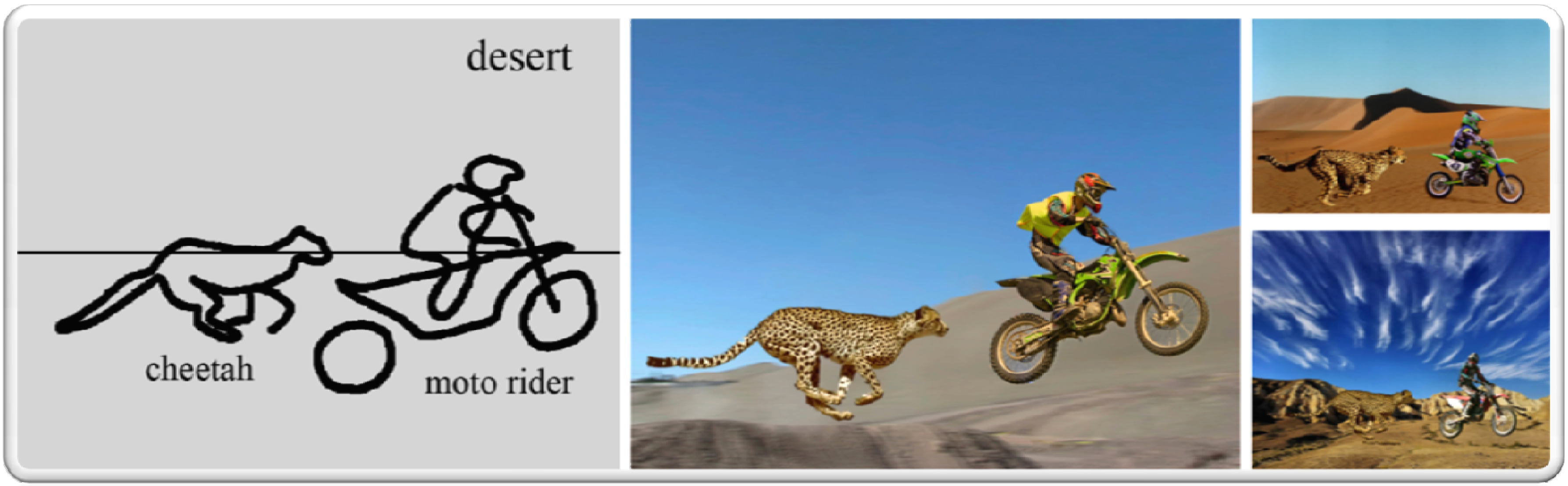
- Extensive filtering work only because we have ***the Internet***

Composition

Source Image

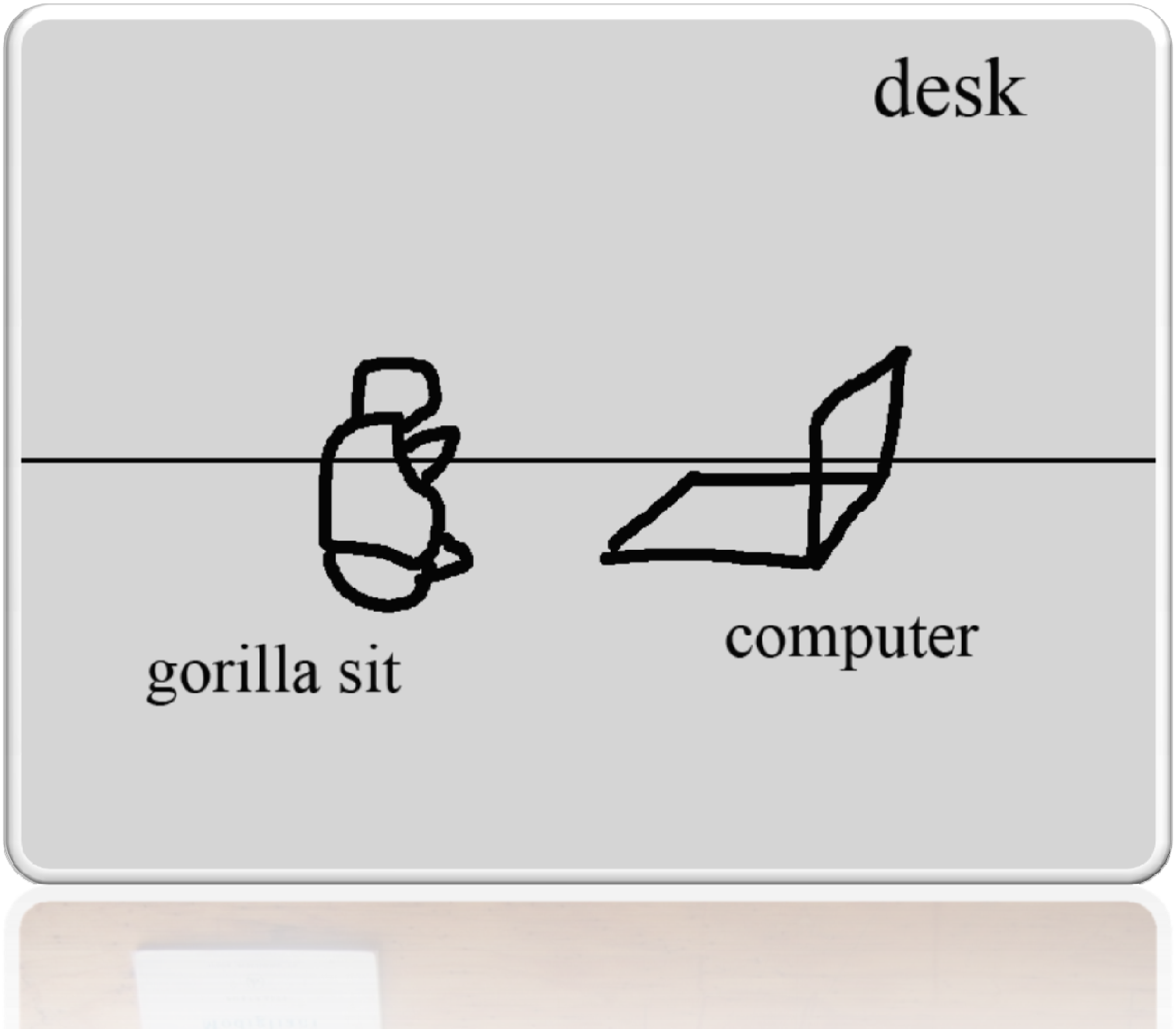
Target Image

Takes Time…



And…

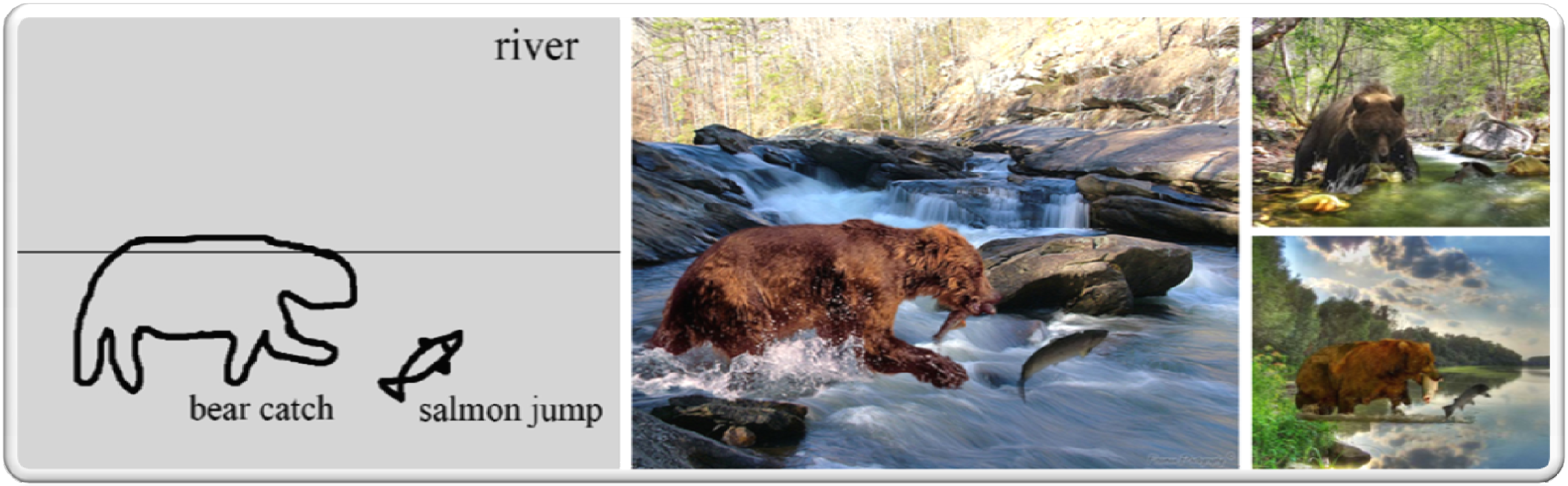
Not Always a Success



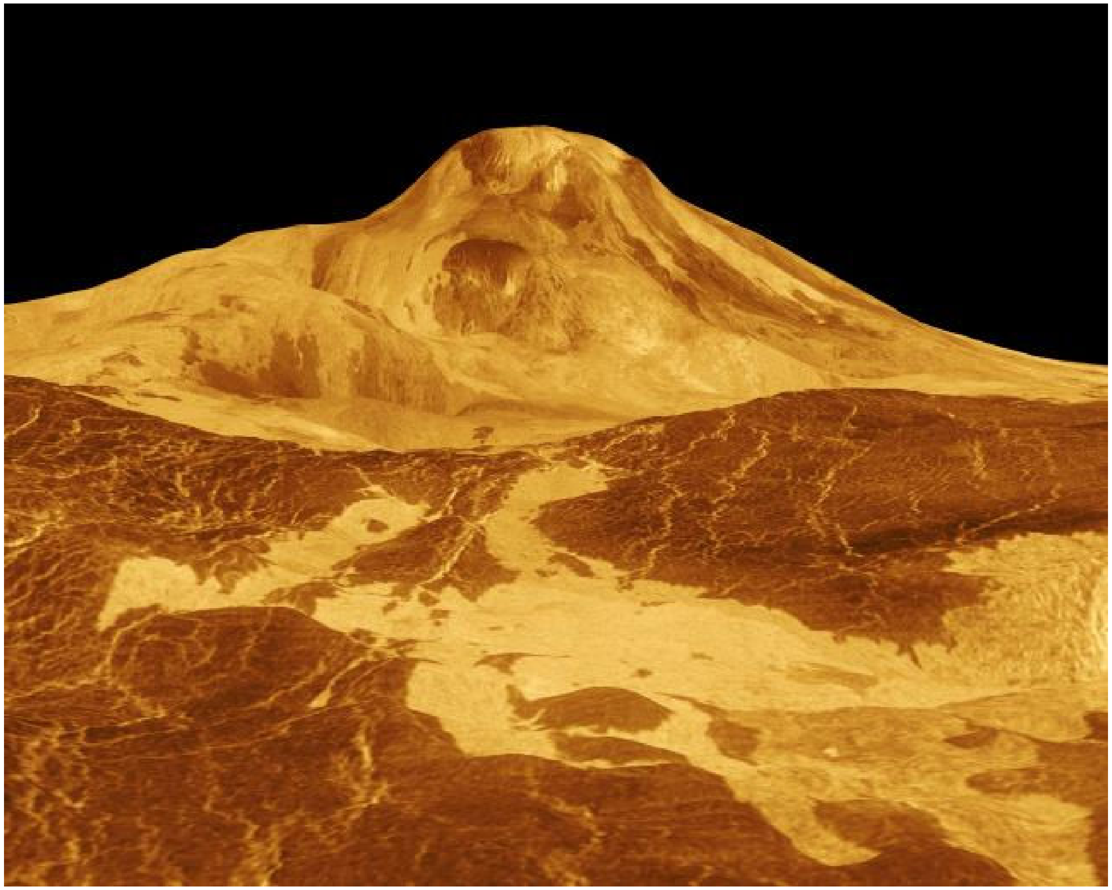
More Results

More Results

More Results



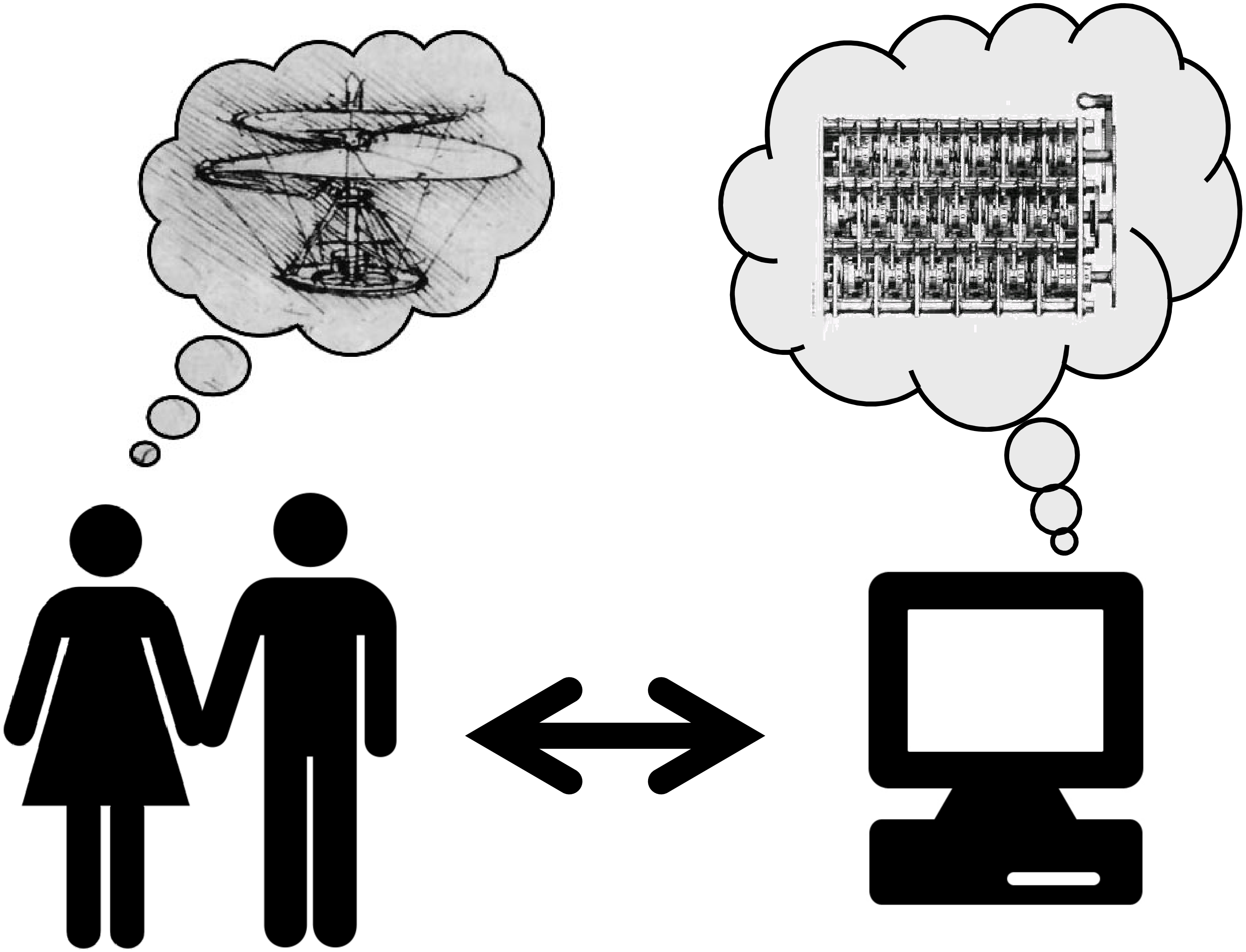
Do images convey reality?



Maat Mons on Venus

Vertical exaggeration of 22.5 times

http://photojournal.jpl.nasa.gov/catalog/pia00254



More information:
http://www.faculty.idc.ac.il/arik/